

The Point of Attack: Where and Why Does Oil Cause Armed Conflict in Africa?*

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First draft: May 2022

This Draft: September 2023

Abstract

Prominent theories of conflict argue that belligerents fight to capture valuable rents, so-called “prizes,” such as oil and other natural resources. Yet, we show that armed groups rarely attack those sites with the most oil above or below ground, oil terminals and wells; only pipelines increase the probability of armed conflict. To explain this finding, we integrate crisis bargaining and Blotto games. In our model, armed groups attack to steal oil and signal their strength; anticipating the government’s defenses, these groups rarely target the most valuable prizes, which are more heavily fortified. Consistent with our model, we also show that armed groups strategically randomize where they attack pipelines and that local and export prices for fuel have different effects on violence, because only export prices affect the government’s willingness to buy off would-be attackers. Our findings provide a rare real-world validation of Blotto games: groups fight to capture resources, but the points of attack are often less valuable and more sporadically defended targets. The findings help resolve debates about oil and conflict and raise new questions about conflict theories writ large.

JEL classifications: D74, Q34

*We thank Sondra Wood and Wood Mackenzie for providing data access and Avery Do for his help wrangling those data. Blair acknowledges funding from the National Science Foundation (SES-1226228). We are grateful to Francisco Garfias, Kevin Grieco, Alexandra Hartman, Tom Palfrey, Aaron Rudkin, Tara Slough, Frank Wyer for their comments, and to conference and seminar participants at Strategy and the Business Environment, UCLA, UC Berkeley, Caltech, Harvard, SITE Political Economic Theory, and APSA for their feedback.

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Much theoretical and empirical work explains civil conflict as a contest over the control of valuable rents, so-called “prizes” (e.g., Bates et al. 2002; Garfinkel and Skaperdas 2007; Laitin 2007; Besley and Persson 2011). Grossman (1995: 193) defines an insurrection simply as a “conflict over the control of property and income.” Oil rents represent one lucrative, contested prize (Fearon 2005; Morelli and Rohner 2015).¹ Consistent with this logic, scholars have found a cross-national correlation between oil extraction and armed conflict (e.g., Lei and Michaels 2014; see Ross 2015 for a review). Others have shown that armed conflict and separatist wars are concentrated in countries’ oil-producing provinces (Asal et al. 2016; Paine 2019).

Contrary to a simple prize logic, however, we find that the biggest prizes are *not* the points of attack: the sites with the most oil above and below ground are not where most armed conflict occurs. Using panel data on the location of oil infrastructure (oil fields, wells, pipelines, and terminals) and armed conflicts across Africa, we show that only pipelines increase the likelihood of armed conflict. We employ a triple-difference empirical strategy to demonstrate that a pipeline coming online raises the probability of armed conflict above and beyond the negligible changes induced by building more critical oil infrastructure. Pipelines more than double the base rate of conflict — an effect many times larger than the minimal effects of oil fields, wells, or terminals.

To explain this finding and reconcile it with past work, we develop a game-theoretic model. The model integrates two common frameworks for understanding armed conflict: a Blotto game in which belligerents choose where to deploy forces across multiple “battlefields,” (Roberson 2006) and a crisis-bargaining game with incomplete information (Fearon 1995). Our analysis of the model provides four observable implications for which we find empirical support.

First, both the government and non-state armed groups want to behave unpredictably. If the government knew where the armed groups were going to strike, they could station their defenses at those locations and fend off attacks. On the other side, if armed groups knew where the government was going to locate its defenses, they would evade those forces and attack unguarded targets. Intentional unpredictability implies that we should observe little correlation over time in the location of attacks because, if armed groups attacked the same sites year after year, the government would know where to station its forces. We show empirically that violence along pipelines is not autocorrelated. Knowing where non-state armed groups previously attacked the pipeline is not a good predictor of their future targets. By contrast, we show that protests and riots have a much higher degree of autocorrelation — the sites of protests tend to be the sites of past protests.

Second, for both sides to be unpredictable, they play mixed strategies in equilibrium. Thus, the government (armed group) is indifferent between defending (attacking) any two targets. All else equal, armed groups want to attack the most valuable targets — in our application, more

1. Other research suggests a different logic, arguing that oil-rich leaders under-invest in state capacity and, thus, are more vulnerable to insurgency (e.g., Fearon and Laitin 2003), but see Glynn (2009) for contradictory evidence.

critical oil infrastructure, such as terminals or wells — but in equilibrium the government defends those larger prizes with higher probability, leaving the group indifferent between attacking critical infrastructure and more sporadically defended sections of pipeline. For its part, the government (all else equal) wants to defend its critical infrastructure, but in equilibrium the armed groups attack pipelines with greater probability, leaving the government indifferent between defending critical and peripheral infrastructure. Overall, this dynamic explains our initial finding, which is that armed groups target the less valuable, but also less consistently defended pipelines. Anticipating that defenses will be stationed around more critical oil infrastructure, armed groups wield a “weapon of the weak” (a la Scott 1985) and sabotage pipelines instead.²

Third, why does the government not strike a deal with would-be attackers to prevent sabotage? We argue that the government would like to bargain away conflict but has incomplete information about whether a group — one of the many making demands of the state — constitutes a real threat (Walter 2009). Thus, the armed groups use attacks against infrastructure as costly signals of their capacity to compel government concessions.³ This dynamic creates two incentives for armed groups to attack. The groups can directly benefit from looting oil (which we call their *prize incentive*) and indirectly from extorting the government (their *signaling incentive*). This matches qualitative evidence from Nigeria and other cases, where rebel groups sabotage pipelines to both pilfer oil and bring the government to the bargaining table. The Nigerian government and oil companies have provided payouts to armed groups who commit to peace, at one point paying lucrative security contracts to the same groups that had been sabotaging the pipelines (see Rexer and Hvinden 2020).⁴

Fourth, our theoretical analysis illustrates how changes in oil prices modulate these incentives and affect the likelihood of attacks. When the value of oil to armed groups increases, all else equal their prize incentives increase, leading to more violence. When the value of oil to the government increases, all else equal it is more eager to avoid sabotage and willing to offer larger concessions — a force that has received less attention in the literature on commodity price shocks, which focuses on how rising oil prices increase the returns to predation (Dube and Vargas 2013). This amplifies armed groups’ signaling incentive, but larger payouts also help to “bargain away” conflict. As such, we show theoretically that increases in the rebel’s value of oil should be more conflict-enhancing than increases in the government’s value. Furthermore, we document evidence of this relationship

2. Oil-rich governments can afford military hardware giving them the upper hand in conventional warfare (Cotet and Tsui 2013; Wright et al. 2015; Paine 2016). Scott (1985) argues that theft and sabotage are tactics used by weaker groups who cannot survive a direct confrontation with the state.

3. Past research on civil war (Fearon 1995; Walter 2009) and terrorism (Kydd and Walter 2006) argues that beligerents use violence to signal their capacity or resolve. Thomas (2014) finds that armed groups perpetrating terror attacks during civil wars are more likely to participate in negotiations and are offered more concessions.

4. This dynamic is present in cases beyond Nigeria. In Appendix Section D, we provide vignettes from Colombia, Egypt, Mexico, and Turkey.

empirically. To proxy for the rebel’s value of oil, we use local prices for gasoline, as stolen oil is often illegally refined and sold on the black market, and we use export (i.e., world) gasoline prices to measure the government’s value. We demonstrate that increases in the local fuel price generally lead to more attacks on pipelines, whereas increases in the global price generally lead to a lower probability of attacks.

This research helps advance the literature on conflict in several ways. First, we show that the points of attack are often not the largest prizes but rather less valuable targets. The prize logic is not unfounded — armed groups fight to capture revenues — but it omits the government’s strategic response. Armed groups anticipate that high-value targets will be well-defended and can only credibly threaten violence if they can locate “battlefields” where they can hope to prevail (e.g., soft targets; rough, unassailable terrain). This insight helps explain why fortified off-shore oil platforms do not provoke conflict (Lujala 2010; Ross 2012; Andersen et al. 2022).⁵ It also helps to reconcile competing claims about the effects of oil on armed conflict. Some argue that resource revenues represent a tempting prize (Laitin 2007), but others claim that those revenues can be invested in military capacity or payouts that deter insurgents (Cotet and Tsui 2013; Wright et al. 2015). We show both can be true. Oil provides a material incentive to fight, but armed groups battle on the periphery to avoid confronting well-equipped security forces. Like Paine (2016), our framework generates this dynamic by modeling how governments defend and armed groups attack anticipating each other’s strategies (see also Dal Bó and Dal Bó 2011 who also endogenize the government’s defenses against predation).

Second, we argue that pipeline sabotage is not just looting by “greedy rebels” (Collier and Hoeffler 2004). These attacks send costly signals to the government and, in doing so, can induce bargaining to address armed groups’ grievances. The point of attacks can, thus, be both “greed” and “grievance.” Indeed, our model shows aggrieved groups can only credibly threaten the government where they have a direct material incentive to attack oil infrastructure.⁶ If even the strongest armed groups derive no direct benefits from attacking, the government anticipates that violence will flame out and offers no concessions.⁷ Greed enables armed groups and communities they draw from to make compelling demands for redress of grievances.

Third, we provide credible estimates of the effect of oil infrastructure on the probability of armed conflict. We do so using a two-way fixed effects design drawing on detailed and previously

5. Moreover, our work implies that lootability, i.e., how easily resources can be appropriated, is not a commodity-specific feature as is commonly assumed in empirical work (Blair et al. 2021). The same commodity may be more or less easily looted in different places.

6. Hoeffler (2011) offers another argument for why “greed” and “grievance” are complementary explanations: grievance redress through rebellion is a club good, and rebel leaders need to offer selective material incentives to recruits (see also Cederman and Vogt 2017).

7. We focus on material incentives, but benefits could also arise from advancing an ideology or the “pleasure of agency” (Wood 2003).

unexploited data from the oil industry research firm Wood Mackenzie. The data provide the timing and location of oil fields, wells, terminals, and pipelines across Africa up to 2014. Previous studies either rely on country-year data that do not capture the local footprint of oil extraction (as in Ross and Mahdavi 2015) or exploit time-invariant data on subsurface deposits (as in Lujala 2010), raising the risk of confounding by unit-specific, time-invariant differences. We sharpen causal identification of our effects by ruling out bias from “forbidden” comparisons recently identified in difference-in-difference designs with staggered treatment timing (e.g., Callaway and Sant’Anna 2020; Goodman-Bacon 2021; De Chaisemartin and d’Haultfoeuille 2020) and by assessing the risk of bias from a key time-varying confound, the construction of roads. Our triple-difference design further buttresses our parallel trends assumption, adjusting for potential selection into areas with shifting conflict rates.

Finally, our data enable us to provide one of the few real-world validations of the Blotto logic (see also Sonin and Wright 2019 on how armed groups time attacks). Most prior empirical studies of Blotto-style interactions rely instead on lab experiments (Dechenaux et al. 2015; Kimbrough et al. 2020; Holt and Palfrey 2022).⁸ A key step is developing a tractable Blotto model in which the values of winning or losing vary across battlefields, and equilibrium strategies and expected utilities are derived in closed-form.⁹

1. Motivating Case

Nigeria is the largest oil producer in Africa, and oil exports make up two-thirds of government revenues (Initiative 2021). During a particularly violent period in 2008, sabotage of the country’s oil infrastructure deprived the state of at least USD 24 billion, a loss on the order of all government expenditure in the previous year (Adibe et al. 2018).¹⁰ We use this well-documented case to illustrate the strategic considerations affecting the sabotage and defense of oil infrastructure. The formal model we develop in the next section helps to rationalize the outcomes — both the armed groups’ behavior and the government’s response — that we observe in Nigeria and other oil-producing low- and middle-income countries.

Nigeria’s onshore oil infrastructure is dominated by long stretches of pipelines and a smaller number of active oil fields, producing wellheads, and active onshore oil terminals. According to

8. Case studies of Nigeria and other oil-producing states describe critical infrastructure as heavily fortified. This is inconsistent with one alternative explanation, namely that armed groups lack the capacity or expertise to exploit critical infrastructure. If that were true, governments would not bother protecting critical sites and expend resources defending pipelines, which we do not observe.

9. This is most similar to Powell (2007), but here we are able to characterize the equilibrium in closed-form and study comparative statics regarding the degree of asymmetry between high- and low-value targets. Like Hart (2008), we focus on a discrete Blotto model. Like Sonin and Wright (2019), the conflict technology is asymmetric where non-state armed groups’ attacks are only successful against undefended sections.

10. See Obi and Rustad (2011) and Watts and Ibaba (2011) for more detailed accounts of oil-related conflict in Nigeria.

data from the Nigerian National Oil Spill Detection and Response Agency, most sabotage (94%) takes place along the pipelines. Few attacks take place near oil terminals (0.3%) or wells (6%). Oriola et al. (2013: 84) observe that non-state armed groups give “serious consideration... to the level of security at potential targets” when planning attacks on oil infrastructure. The length and location of pipelines make them easy targets: “with endless miles of undefended oil pipelines crisscrossing the Niger Delta, militants are able to commit acts of sabotage and oil theft at will” (Asuni 2009: 26).

Security forces focus on more compact and valuable oil infrastructure. The Joint Task Force, a military unit charged with protecting Nigeria’s oil and gas facilities, guards terminals and oil platforms, supplementing the private security employed by oil companies. For example, the chief military commander for the region reported, “[c]ritical oil platforms have troops deployed on them round the clock to ensure their protection” (Oyadongha 2014). He described the difficulty of protecting the pipelines because these attacks take place “mostly in remote areas of the creeks carried out at night between 2300hrs to 0300hrs by criminal gangs who take advantage of the JTF’s limited accessibility.”

Militant groups, to varying degrees, have two motivations when launching these attacks. First, they sell stolen crude oil and illegally refined fuel on the black market, earning a local price well below the oil’s market value (Oriola et al. 2013: 80). Not all the militant groups are involved in oil theft operations, but most groups are involved in some way by tapping into pipelines, financing and managing small-scale refineries, or selling fuel (Katsouris and Sayne 2013).

Second, they use attacks to respond to unaddressed poverty and environmental degradation in Nigeria’s oil-producing regions (Eke 2015; Onuoha 2008; Ukiwo 2007). Ukeje (2001: 346) writes:

[E]xpressing community grievances and even very legitimate social demands often produced limited response from oil company executives or government officials, or occasionally evoked outright indignation and hostility. Having failed to win any concessions or developmental projects through peaceful means, militant youth groups then seized flow stations, rigs, and other oil installations, and held local and expatriate oil company staff hostage.

Groups sabotage oil infrastructure to force the state to respond to their social, economic, and environmental demands (Onuoha 2008; Watts and Ibaba 2011; Oriola et al. 2013). For example, the large Nembe pipeline carried 130,000 barrels per day when it was attacked in July 2008. The Movement for the Emancipation of the Niger Delta (MEND) claimed credit (Wosu 2008). MEND’s spokesperson tied its attacks to grievances in the Niger Delta:

[MEND] will continue to nibble everyday at the oil infrastructure in Nigeria until the oil exports reaches zero. At such a time, we expect the government to take seriously our demands of effecting true federalism, including fiscal federalism as practiced in all genuine federal republics around the world (Amaize and Oyadongha 2008).

The demand for “fiscal federalism” is a call for more oil revenues to be allocated to Nigeria’s oil-producing regions.

While sabotage is costly for both sides, there is a pervasive sense that the government will not seriously bargain until attacked: “the militias know that this government only listens to violence” (USAID 2006: 37). Eke (2015: 757) calls this the “rule of muscle:” violence is seen as the only way to garner a response. From the state’s perspective, mounting an attack appears to differentiate those groups which they feel must be granted a concession to curb sabotage.

Once convinced of the threat, the Nigerian government has been willing to buy off its attackers. Following a spate of attacks from 2007 to 2008, the government signed an amnesty agreement in 2009 with militant leaders that called for financial payments and disarmament. In practice, few working weapons were turned in (Hazen and Horner 2007), and most of the money went to the several top leaders who led oil infrastructure attacks in their regions of influence (Obi 2014). Top commanders accepted the amnesty at ceremonial meetings in Abuja and in the Niger Delta and, according to U.S. Embassy cables at the time, received large payments in return for doing so (Lagos 2009). Monthly salary payments of USD 400 also began for rank-and-file militants as well as job training programs, though implementation was mixed. Oil production immediately began to rebound: the Minister of Petroleum Resources, Rilwan Lukman, tied the amnesty agreement to an increase in oil production from 1.2 million barrels per day to 1.7 million per day shortly after the agreement (Staff 2009).

The government began paying many of the same militant commanders pipeline protection contracts in 2012. Described by Eke (2015: 756) as an attempt to “buy peace in the Niger Delta,” the government offered contracts to militants totaling over 6 billion Naira (roughly USD 40 million). At least in the medium term, these payoffs appear to have reduced violence. Rexer and Hvinden (2020: 5) find that “areas controlled by rebels who received surveillance contracts see a nearly 75% reduction in oil theft.” Even critics of the contracts note that attacks declined and production increased (Adibe et al. 2018).

Oil companies have adopted strategies similar to the state. Amunwa (2012: 8) reports, “Oil companies have regularly made ‘stay-at-home’ payments to armed groups. . . Shell frequently uses payments and contracts to pacify armed groups and to regain access to oil facilities closed or damaged by the conflict.” The report describes an episode in which Shell made repeated visits to a community where armed groups were competing for turf. During each visit, the company

“allegedly paid whichever faction [currently] controlled access to the area.” Payments were in proportion to the groups’ threat to oil infrastructure: “If you negotiate with an AK-47 they will pay you a price for that, with a pistol, a bazooka, a gunboat [...] they will pay you based on your coercive power” (Zalik 2011).

Several features of this case inform assumptions or accord with implications from the formal model we develop below. Militants attack oil pipelines, which are less valuable but also more weakly defended than export terminals or wellheads. These groups have multiple motivations. Pilfered oil and illegally refined fuel can be sold on black markets (the prize incentive), and sabotage brings the government to the bargaining table (the signaling incentive). Consistent with costly signaling, the state and oil companies respond to violence, buying off those groups with the demonstrated capacity to sabotage oil infrastructure. The state will pay for peace but only after it is convinced that armed groups will disrupt oil production.

Pipeline sabotage and payouts to saboteurs are not unique to Nigeria. Giroux et al. (2013) identify 27 countries with over ten attacks on oil and gas infrastructure from 1980–2013; six countries saw more than one hundred attacks. Oil theft is common and substantial across these states. It has been documented in Angola, Iran, Iraq, Libya, Mexico, Nigeria, Pakistan, Russia, and Syria; smuggling has been observed in many more, including Ghana and Morocco (Katsouris and Sayne 2013; Nellemann et al. 2018). By some estimates, global oil theft amounts to roughly USD 20 billion and accounts for a fifth of revenues accruing to armed groups and organized crime (Nellemann et al. 2018). In Appendix Section D, we provide brief accounts from other cases (Colombia, Egypt, Mexico, and Turkey) where, as in Nigeria, groups have focused attacks pipelines to steal fuel or garner concessions.

2. Theoretical Framework

We integrate two common strategic interactions between a government (G) and an armed group (A): a Blotto game with attack and defense across multiple conflict sites and crisis bargaining amid incomplete information. We introduce the Blotto-style model then use its equilibrium expected payoffs as the disagreement payoffs in a bargaining model with incomplete information and costly signaling.

2.1 One-shot Blotto Game: Sabotage of Oil Infrastructure

The oil infrastructure is comprised of $N \geq 2$ sections, categorized into two types. There are $N^c \geq 1$ critical pieces that represent high-value, costly repaired targets such as oil wells or terminals. There are $N^p \geq 1$ pieces of oil pipeline, which are low-value, cheaply repaired targets. We order the infrastructure such that $n = 1, \dots, N^c$ indexes the critical pieces and $n = N^c + 1, \dots, N$ indexes the pipelines, where $N^c + N^p = N$.

The two actors simultaneously decide what infrastructure sections to defend and attack. The government has enough resources to defend S^G sections, where $1 \leq S^G < N$.¹¹ So its choice is a vector of defense locations $l^G = (l_1^G, \dots, l_N^G) \in \{x \in \{0, 1\}^N \mid \sum_n x_n = S^G\} \equiv \mathcal{L}^G$ such that $l_n^G = 1$ means the government defends section n and $l_n^G = 0$ means the government leaves section n undefended. The armed group has enough resources to attack S^A sections where $1 \leq S^A < N$; its choice is a vector of attack locations $l^A = (l_1^A, \dots, l_N^A) \in \{x \in \{0, 1\}^N \mid \sum_n x_n = S^A\} \equiv \mathcal{L}^A$, where $l_n^A = 1$ means the group attacks section n and $l_n^A = 0$ means it does not attack section n .

Given a profile of defense and attack locations $l = (l^G, l^A)$, the group successfully sabotages section n if and only if it attacks n and n is undefended. This contest success function reflects a common asymmetry in military capacity where the weaker armed group is surely defeated when facing the government head on.¹² Specifically, payoffs from section n given locations are

$$\pi_n^G(l_n^G, l_n^A) = \begin{cases} -\theta v^G \cdot l_n^A \cdot (1 - l_n^G) & \text{if } n \leq N^c \\ -v^G \cdot l_n^A \cdot (1 - l_n^G) & \text{if } n > N^c \end{cases}$$

for the government and

$$\pi_n^A(l_n^G, l_n^A) = \begin{cases} \theta v^A \cdot l_n^A \cdot (1 - l_n^G) & \text{if } n \leq N^c \\ v^A \cdot l_n^A \cdot (1 - l_n^G) & \text{if } n > N^c \end{cases}$$

for the armed group. Total payoffs for actor i are $\Pi^i(l) = \sum_n \pi_n^i(l_n^G, l_n^A)$. In the expression above, $v^G > 0$ represents the government's loss after a successful pipeline attack. It captures the value of stolen oil and costs of repairs. Likewise, $v^A > 0$ represents the group's gain after a successful attack. These gains include the value of stolen oil, often sold on black markets or refined into diesel or kerosene for local sale. The gains also include expressive benefits from successful sabotage.

The parameter $\theta > 1$ captures the asymmetric value between pipelines and critical pieces. When θ is large, critical infrastructure holds substantially more oil and is more costly to repair than pipeline sections. When θ is closer to 1, that asymmetry is muted. Because $\theta > 1$, absent government defenses, the group prefers to attack critical over pipeline sections. Likewise, the government prioritizes defense of critical rather than pipeline sections if both are attacked with equal probability.

A strategy for actor i is a probability distribution $\sigma^i \in \Delta(\mathcal{L}^i)$, where $\sigma^i(l^i)$ is the probability that i chooses location vector $l^i \in \mathcal{L}^i$ and $\Delta(\mathcal{L}^i)$ is the $\#\mathcal{L}^i$ probability simplex. Let $U^i(\sigma)$ denote

11. In many oil-producing states, the government collaborates with extractive companies to secure oil infrastructure. We treat these parties as a unified actor, and S^G represents their total defensive resources.

12. Each actor can locate at most one unit of force at each section. This is without loss of generality, as our contest success function eliminates incentives for the government or armed group to locate more than one unit of force at any section.

i 's expected payoffs given σ where

$$U^i(\sigma) = \sum_{l^G \in \mathcal{L}^G} \sum_{l^A \in \mathcal{L}^A} \sigma^G(l^G) \sigma^A(l^A) \Pi^i(l^G, l^A).$$

We characterize Nash equilibria of the game. To do this, let $s_n^i(\sigma^i)$ denote the probability that i locates at section n given strategy σ^i which means $s_n^i(\sigma^i) = \sum_{l^i \in \mathcal{L}^i} \sigma^i(l^i) \cdot l_n^i$. At times, we suppress notation and write s_n^i instead of $s_n^i(\sigma^i)$ when it is clear that s_n^i depends on σ^i . In words, s^i is a marginal distribution of strategy σ^i and, thus, a simpler summary of the strategy. We say an equilibrium is fully mixed if the government and the armed group locate at each section n with probability between zero and one.

Definition I. Profile σ is fully mixed if the government and armed group locate at each section with probability strictly between zero and one, that is, $s_n^i \in (0, 1)$ for all i and n .

The next result characterizes the marginal distributions and expected utilities in every fully mixed equilibrium. Its proof, and those of the proceeding results, are in Appendix E.

Proposition I. In a fully mixed equilibrium σ , the probability that the government defends and the probability that the group attacks section n are

$$s_n^G = \begin{cases} \frac{S^G + (\theta - 1)N^P}{N^c + \theta N^P} & \text{if } n \leq N^c \\ \frac{N^c + \theta(S^G - N^c)}{N^c + \theta N^P} & \text{if } n > N^c \end{cases} \quad \text{and} \quad s_n^A = \begin{cases} \frac{S^A}{N^c + \theta N^P} & \text{if } n \leq N^c \\ \frac{\theta S^A}{N^c + \theta N^P} & \text{if } n > N^c \end{cases},$$

respectively. Furthermore, expected utilities are

$$W^G = -\frac{\theta(N - S^G)S^A v^G}{N^c + \theta N^P} \quad \text{and} \quad W^A = \frac{\theta(N - S^G)S^A v^A}{N^c + \theta N^P}.$$

Using the characterization of fully mixed equilibria in Proposition I, Implication I summarizes our predictions about attacks on different infrastructure types.

Implication I. The following hold in every fully mixed equilibrium σ :

1. Every pipeline section is more likely to be attacked than every critical section. That is, for all $n \leq N^c$ and $n' > N^c$, $0 < s_n^A < s_{n'}^A$.
2. Let $P^P = \frac{\theta S^A}{N^c + \theta N^P}$ denote the probability of an attack on a pipeline section. It is strictly increasing in θ , and $\lim_{\theta \rightarrow \infty} P^P = \frac{S^A}{N^P}$.
3. Let $P^c = \frac{S^A}{N^c + \theta N^P}$ denote the probability of an attack on a critical section. It is strictly decreasing in θ and $\lim_{\theta \rightarrow \infty} P^c = 0$.

Implication I says that most valuable targets are the least likely point of attack in equilibrium.¹³ Furthermore, when the value of these targets is highly asymmetric (i.e., θ is large), we do not expect to see attacks on the more critical infrastructure.

To see the logic behind this, note that each actor is indifferent between locating at any two sections in a fully mixed equilibrium. When θ increases, critical infrastructure becomes a more attractive prize for the group and a greater vulnerability for the government, all else equal. To maintain the armed groups's indifference condition, the government increases the likelihood that it defends the critical infrastructure and reduces the likelihood that it defends pipeline sections. To maintain the government's indifference condition, the group becomes less likely to attack the critical infrastructure and more likely to attack the pipeline sections.

One might argue that armed groups focus attacks on pipelines because attacks against critical pieces are strictly dominated due to forces outside of the Blotto interaction. For example, insurgent groups might lack the equipment or expertise to steal oil from wells or terminals, or attacking critical pieces might permanently and irreparably damage oil infrastructure, among other explanations. Such arguments ignore how governments would best respond to groups ignoring critical pieces, however. If attacking these pieces were strictly dominated, then governments should anticipate that armed groups will only attack pipelines, and hence they should allocate their forces at pipelines instead of critical pieces to reduce the likelihood of successful attacks. We observe the opposite behavior from governments in our case studies. Specifically, governments typically fortify critical infrastructure — in Nigeria, groups anticipate that oil platforms receive close to round-the-clock protection from specialized military units — and leave pipelines relatively unguarded. Given how the government allocates its defenses in practice, it is implausible that armed groups strictly prefer to attack pipelines over critical pieces all else equal.

Hence, the asymmetry parameter potentially varies by actor with $\theta^G > 1 > \theta^A$, so the group receives a smaller prize from successfully attacking critical pieces than pipelines. This change does not affect the model's predictions about militants' attacks though because the government still receives a larger loss from attacks against critical rather pipeline pieces. When $\theta^G > 1$, the group must be attacking pipeline pieces with higher probabilities than critical pieces in any fully mixed equilibrium, because in such an equilibrium, the government must be indifferent between defending a critical versus a pipeline piece. This prediction does not depend on θ^A .

Implication II. *In every fully mixed equilibrium σ , the armed group attacks all pipeline sections with equal probability.*

13. A version of Implication I still holds when we focus on *successful* attacks, i.e., $(1 - s_n^G)s_n^A$ instead of attacks, s_n^A .

Finally, armed groups do not focus on a single segment of infrastructure. If they did, then the government would relocate its defenses to ward off attacks. Likewise, the government does not surely defend any one section of the infrastructure. If it did, the group would anticipate this and attack elsewhere. The final result demonstrates that, under reasonable conditions, a fully mixed equilibrium exists and all equilibria are fully mixed.

Proposition II. *A fully mixed equilibrium exists if and only if $S^G > \frac{\theta-1}{\theta}N^c$ and $S^A < \frac{N^c+\theta N^p}{\theta}$. Moreover, if a fully mixed equilibrium exists, then all equilibria are fully mixed.*

Proposition II states two conditions that are jointly sufficient and individually necessary for fully mixed equilibria to be relevant. The first requires the government to be strong enough that it can defend at least $\frac{\theta-1}{\theta}N^c$ sections. This holds for all $\theta > 1$ if $S^G \geq N^c$, i.e., the government can defend the critical infrastructure. The condition likely holds because, absent it, oil companies would be reluctant to build any critical oil infrastructure in a country. The second condition requires that the armed group is not too strong and can only attack less than $N^p + \frac{N^c}{\theta}$ sections. This holds for all θ if $S^A \leq N^p$, which means that the group cannot attack every section of the pipeline simultaneously.

2.2 Bargaining

We now consider an ultimatum-bargaining model in which the payoffs from the Blotto game represent each actor's reservation value.¹⁴ More specifically, the government offers some payment to the armed group $x \geq 0$, and the group decides to accept or reject. After accepting, payoffs are $-x$ and x for the government and group, respectively. After rejecting, payoffs are W^G and $W^A - c$ for the government and group, respectively.

The value c is the group's cost of attacking the oil infrastructure and is private information. This cost is drawn from the uniform distribution over $[0, C]$ at the beginning of the interaction, and $C > 0$ is an exogenous parameter. The cost c can be thought of as the inverse of group strength, where strong groups can more easily mobilize their troops to attack. In addition, notice the group's value of attacking is $W^A - c$, so c can also be interpreted as an internal, temporary shock to the cost of selling oil on the black market.

We view group strength as two dimensional, (S^A, c) . The first dimension S^A represents the number of sections the group can attack. The second dimension c is the cost of mobilizing its forces or, alternatively, the expected cost of refining and processing stolen oil. This setup assumes that c is a dimension of group strength that is not easily known to the government, whereas S^A , which likely correlates with the group's size, is more easily observed. The next assumption says the government has more to lose from the oil-sabotage game than the armed group has to gain.

14. As such, we are implicitly assuming that the sufficient conditions in Proposition II hold.

Assumption I. *The government wants to avoid conflict: $v_G > v_A$.*

Assumption I implies $0 < W^A < -W^G$, i.e., the government would grant some transfers to the group if it knew it faced the strongest type ($c = 0$). We maintain this assumption in the next analysis for two reasons. First, after successful attacks against oil infrastructure, the government incurs costs unrelated to the stolen oil such as the cost of repairs. Second, armed groups most likely sell stolen crude or refined oil on the black market, and leaving the formal economy typically diminishes their value. The next result characterizes the subgame perfect Nash equilibrium of the bargaining game. We omit the proof which follows standard logic for these models.

Proposition III. *In the bargaining game, the armed group accepts an offer if and only if $x \geq W^A - c$. The government offers*

$$\chi = \begin{cases} 0 & \text{if } C \geq W^A - W^G \\ \frac{1}{2}(W^A - W^G - C) & \text{if } C \in (-W^A - W^G, W^A - W^G) \\ W^A & \text{if } C \leq -W^A - W^G \end{cases}$$

The standard risk-reward tradeoff emerges. When $W^A \leq c$, attacking oil infrastructure is not profitable for the group, so it accepts every offer. As C increases, so too does the probability that attacks are unprofitable for the group even if the government makes a low offer. The government thus reduces its offer as C increases.

Corollary I (Fighting costs and the government's optimal offer). *If $C \geq W^A - W^G$, then the government's optimal offer is zero. If $C < W^A - W^G$, then the government offers some transfers to the armed group.*

2.3 Signaling before Bargaining

Finally, we consider a model in which armed groups can attack before bargaining to signal their strength. Specifically, the interaction proceeds over three phases:

1. The group observes its private information c and decides whether to attack $a_1 = 1$ or not $a_1 = 0$.
2. The government observes a_1 and makes an offer $x \geq 0$.
3. The group either rejects the offer and attacks $a_2 = 1$ or accepts the offer and does not attack $a_2 = 0$.

Payoffs from this game are as follows:

$$u^A(a, x, c) = (a_1 + a_2)[W^A - c] + (1 - a_2)x \quad \text{and} \quad u^G(a, x, c) = (a_1 + a_2)W^G - (1 - a_2)x.$$

Every time the group attacks, it pays cost c and then both actors accrue payoffs derived from the Blotto game. If the group accepts the government's offer, no second attack occurs and the government transfers x to the group. We maintain the assumption c is drawn from the uniform distribution over $[0, C]$ at the game's start.¹⁵ The next result characterizes perfect Bayesian equilibria in pure strategies.

Proposition IV. *Assume $C > 2W^A$. The following hold in every pure-strategy equilibrium of the signaling game.*

1. *If there is no initial attack ($a_1 = 0$), the government offers $\chi_0 = 0$. After an initial attack ($a_1 = 1$), the government offers $\chi_1 = \min \left\{ -\frac{1}{3}W^G, W^A \right\}$.*
2. *In phase 1, the armed group attacks if $c < W^A + \chi_1 \equiv c^*$ and does not attack if $c > c^*$. In phase 3, the group accepts offer x if $x > W^A - c$ and rejects if $x < W^A - c$.*
3. *Beliefs are updated via Bayes rules with probability density function:*

$$\mu(c|a_1) = \begin{cases} \frac{1}{C-c^*} & \text{if } a_1 = 0 \text{ and } c \in (c^*, C] \\ \frac{1}{c^*} & \text{if } a_1 = 1 \text{ and } c \in [0, c^*) \\ 0 & \text{if } a_1 = 0, c \notin [c^*, C] \text{ or } a_1 = 1, c \notin [0, c^*] \end{cases}.$$

The cutpoint c^* incorporates two incentives to attack. The value W^A is the prize incentive, i.e., the expected benefits from oil theft. The value χ_1 is the signaling incentive, i.e., the expected value from government concessions. Strong groups with costs $c \leq W^A$ attack because they are able to immediately profit from stealing oil. By contrast, moderately weak groups with costs $c \in (W^A, c^*)$ attack the pipeline even though their attacks are not immediately profitable, i.e., $W^A < c$. Nonetheless, they do so expecting future concessions from the government.¹⁶

Based on Proposition IV, we define two measures of violence: (1) the probability of at least one attack in equilibrium $P_1 = F(W^A + \chi_1)$, and (2) the probability of an attack due to bargaining failure $P_2 = F(W^A - \chi_1)$.

15. This setup implicitly assumes that armed groups are not defeated after an attack. Substantively, this reflects our focus on small-scale conflicts in which groups do not risk their existence by attempting to sabotage oil infrastructure. More technically, note that in a fully mixed equilibrium $\lim_{N \rightarrow \infty} s_n^A s_n^G = 0$ for all sections n . Thus, the probability that the government and armed group confront each other is close to zero when oil pipelines are long.

16. The model implicitly assumes that the government can attribute attacks to a specific group, because, e.g., insurgent or ethnic groups have defined areas of control. This matches our case study of Nigeria where the government and oil companies invested resources to understand the geography of group control. In addition, territorial dominant groups, especially those who have the possibility of attacking, have incentives and resources to monopolize insurgent violence in their neighborhood.

Implication III (Effects of prices on attacks). P_1 and P_2 weakly increase in the armed group's value of a successful attack (v^A). While P_1 weakly increases in the government's cost of successful attack (v^G), P_2 weakly decreases in v^G . That is, $\frac{\partial P_1}{\partial v^A} > \frac{\partial P_1}{\partial v^G} \geq 0$ and $\frac{\partial P_2}{\partial v^A} \geq 0 \geq \frac{\partial P_2}{\partial v^G}$.

The weak inequalities in Implication III hold strictly when $-W^G < 3W^A$. Increasing the group's value oil all else equal exacerbates violence by increasing both the prize and signaling incentives. Marginally weaker groups choose to launch an initial attack, and stronger groups are less likely to accept the government's offer. This effect is always larger than that of a corresponding increase to the government's value of oil. When v^G increases, the government makes weakly larger offers, so there are potentially two countervailing effects: weaker groups are more likely to initially attack in search of a larger payout (i.e., enhanced signaling incentive), but the government makes larger offers, thereby creating a lower likelihood of bargaining failure. Depending on how the phases of the game map to real-world data (e.g., whether we observe an interaction only after phase 1), increases in v^G could actually decrease violence.

Overall, our analysis illustrates how and when governments use side payments to prevent attacks against oil infrastructure, matching the qualitative evidence in the cases above. Nonetheless, governments could also spend these funds on fortifying defenses by increasing their security forces, S^G . Such a tactic would indeed reduce the prize and signaling incentives of attacks as $\frac{\partial W^A}{\partial S^G} < 0$ and $\frac{\partial W^G}{\partial S^G} > 0$. Our model and cases illustrate why the government may be reluctant to pursue such an approach, however. Specifically, when the number of pipelines is large, the peace-enhancing effects of increases in S^G are muted.¹⁷ Intuitively, when pipelines are long, additional security forces will not meaningfully increase the probability that the government prevents attacks by catching evasive armed groups. More than 80% of the countries in our sample have oil infrastructure that includes at least 100 kilometers of pipeline. Algerian infrastructure has the greatest length with 27,540 kilometers of pipelines, and the Ivory Coast has the shortest with 27 kilometers. In these situations, our model suggests that government would prefer to cut bargains with armed groups rather than increase the size of its defensive forces.

2.4 Empirical Implications

We assess the model's implications in a sample of African countries. We want to explain variation in two theoretical quantities: the probability of an attack on a pipeline segment ($P_t P^p$) and critical pieces of infrastructure ($P_t P^c$) in a given period $t \in \{1, 2\}$. We view these quantities as representing the added attack risk from having infrastructure of type c or p in phase t .

H1: *An operational pipeline increases the likelihood of attacks, and this effect exceeds the increase induced by other oil infrastructure.*

17. Formally, $\frac{\partial W^A}{\partial S^G \partial N^p} > 0$, $\frac{\partial W^G}{\partial S^G \partial N^p} < 0$, and $\lim_{N^p \rightarrow \infty} \frac{\partial W^A}{\partial S^G} = \lim_{N^p \rightarrow \infty} \frac{\partial W^G}{\partial S^G} = 0$.

Our first hypothesis follows from Implication I. In fully mixed equilibria (which are the only equilibria under plausible assumptions), pipelines are more likely to be attacked than more critical sections regardless of the values of N^c , N^p or θ . Furthermore, as the asymmetry between the value of the pipeline and more critical infrastructure increases, P^p increases to $S^A/N^c > 0$ and P^c decreases to zero. We expect this asymmetry to be large, so we also expect a pipeline to increase the likelihood of attacks, and higher-value infrastructure to have a smaller, perhaps negligible, effect on violence.

H2: Past attacks do not predict which pipeline sections are later sabotaged.

Following Implication II, our second hypothesis reflects armed groups' deliberate unpredictability. Our final hypothesis describes the effects of oil prices on the likelihood of attacks along pipelines.

H3: An increase in the black-market price of fuel induces a larger increase in attacks than an increase in the export price of fuel does.

In Implication III, increasing the value of oil to armed groups (v^A) has a larger positive effect on violence than increasing the value of oil to the government (v^G). Our third hypothesis, thus, predicts that increases in the black-market price of fuel (our proxy for v^A) will have a larger effect on violence than equivalent increases in the export price (our measure of v^G). We discuss these proxies further below.

3. Data

3.1 Oil and Gas Infrastructure

We use proprietary geo-spatial data on oil and gas infrastructure from the research firm Wood Mackenzie. The data include information on where and when new infrastructure comes online, including oil and gas fields, wells, pipelines, and terminals. Appendix Figure A.1 maps these features up to 2014, the final year for which we have data.

Fields are tracts of land above known reservoirs of oil or gas. Wells (or wellheads) are found within these larger fields and are the specific points at which oil or gas is brought to the surface. We include both exploration wells used to assess the scale and viability of extraction from a field as well as production wells used for extraction. Gathering pipelines bring crude oil or natural gas from wells to processing facilities; larger transmission pipelines move crude and refined products over longer distances (e.g., between countries).¹⁸ Terminals are industrial storage facilities, sometimes attached to refineries, where fuel is collected prior to being loaded on tankers or other delivery vessels. (Our data do not differentiate refineries from other oil and gas terminals.) Fields, wells, and terminals share several attributes relative to pipelines: they are compact features known to store large quantities of oil or gas below or above ground. Control of a wellhead or terminal

18. We include active pipelines and not those planned, under construction, or decommissioned.

implies control over the fuel at that site; hijacking a section of pipeline typically provides a smaller flow that can be remotely interrupted once the sabotage is detected. In the analysis below, we group together fields, wells, and terminals, as these pieces of infrastructure store relatively more value than pipelines and, thus, constitute more critical infrastructure for oil extraction and export (i.e., $\theta > 1$). These types of high-value infrastructure are also less common, and grouping these features improves the precision of our estimates. In our data, the scale of pipelines dwarfs other features. There are 90,000 km of pipelines on the African continent where we focus our analyses, less than 1,000 producing fields, and under 200 terminals as of 2014.

Our data are distinct from previous sources. Most analyses of oil and conflict rely on country-year data on oil exports (Collier and Hoeffler 1998; De Soysa 2002; Fearon and Laitin 2003), production (Humphreys 2005), reserves (Humphreys 2005; Cotet and Tsui 2013), discoveries (Lei and Michaels 2014), or rents (De Soysa and Neumayer 2007). These data can be used to estimate the total effect of oil on conflict at the country level. However, our work and other recent research predict that oil will have varied effects depending on where extraction and refining take place. Lujala (2010) enabled initial tests of these claims by extracting (point) locations of oil fields and their discovery and production dates from the US Geological Survey’s World Petroleum Assessment (see also Denly et al., n.d. who construct a field-year dataset with annual production values). Several studies use these data to relate separatist armed conflicts to oil reserves (e.g., Morelli and Rohner 2015; Asal et al. 2016). Our data improve upon this source in a few ways. We have the boundaries of oil and gas fields, whereas the earlier data used circular, 30-kilometer buffers as an approximation (which is many times larger than the average field). We have dates for individual fields, whereas the earlier data often used the earliest date across several combined fields. Finally, we have data on other types of infrastructure; oil fields are only the start of a long value chain.¹⁹

3.2 Gasoline Prices

Most analyses of oil price changes and conflict do not separately measure the value of oil to government and armed groups (Blair et al. 2021; Dube and Vargas 2013). And these prices can be correlated: for example, the “bush price” of stolen oil in Nigeria is often calculated as a percentage of the market price (Oriola et al. 2013: 80). Prior results do not, thus, allow us to infer whether increases in the world price exacerbate violence along existing pipelines by increasing v^G , v^A , or both.

To make empirical progress, we exploit variation in fuel subsidies. Many oil-producing states subsidize fuel, which creates a wedge between the global price and a lower price that consumers pay at the pump. Stolen oil is often illegally refined and resold locally as gasoline and kerosene,

19. The location of wellheads is particularly informative. Fields may never be exploited due to cost (Owen et al. 2010) or political risk (see Massey and May 2005 on Chad).

and subsidies depress the black-market value of fuel. Consumers will not pay more for stolen gas than the legal, potentially heavily subsidized supply. A 2011 headline about Togo’s decision to curtail its fuel subsidies makes this relationship plain: “Higher Fuel Taxes Driving Togolese Motorists to Black Market” (VoA News 2011). And greater demand for black-market fuel should increase the prize incentive for armed groups. A 2022 report from the International Crisis Group argues that lower subsidies exacerbated pipeline sabotage in Mexico, arguing that “the removal of fuel subsidies [...] increased the returns on theft, attracting more criminals to the business and ratcheting up conflict among them” (International Crisis Group 2022: 3).

We leverage fossil fuel subsidies to analyze whether changes to local and global prices differentially affect armed conflict along pipelines. Ross et al. (2017) measure the wedge between local gasoline prices and the world price at the monthly level from 1997–2014. To construct an annual price, we simply average their monthly data. Between 2003 and 2014 in our sample of countries, the local price of fuel ranged from 31 to 364 percent of the world price (169 percent on average). We use the local fuel price as a proxy for the value of stolen oil for armed groups (v^A). The global price then measures the value of gasoline to the government (v^G).

3.3 Armed Conflict

The Armed Conflict Location and Event Data Project (ACLED) provides event-level data on armed and social conflict from all African countries starting in 1997 (Raleigh et al. 2010). ACLED uses three types of sources: “(1) more information from local, regional, national and continental media is reviewed daily; (2) consistent NGO reports are used to supplement media reporting in hard-to-access cases; (3) Africa-focused news reports and analyses are integrated to supplement daily media reporting” (Raleigh et al. 2017). We only retain events that can be precisely geo-coded (e.g., placed in a specific town). To avoid concern about duplicated events, we code separate indicator variables that take a one if the following occurs: any ACLED event, a battle, a battle involving a rebel group, or a battle involving a rebel group or ethnic militia.²⁰ We focus on the last three outcomes given our interest in armed conflict involving rebels and militants; however, our results are robust to using an indicator for any violent event — a broader classification in ACLED that includes battles, remote violence, and violence against civilians. Unless noted, we omit non-violent actions and demonstrations (i.e., protests and riots), which make up a large share of all ACLED events.

20. ACLED defines a battle as a “violent interaction between two politically organized groups at a particular time and location” (Raleigh et al. 2017: 8). Rebel groups are “political organizations whose goal is to counter an established national governing regime by violent acts” (16). Ethnic (or identity) militias are “groups organized around a collective, common feature including community, ethnicity, region, religion or, in exceptional cases, livelihood” (18). Events involving ethnic militias are often called “communal violence.”

Attacks on oil pipelines are often small clashes that do not involve battle deaths (see Appendix Table A.1 for a set of illustrative conflict events from our data). For this reason, we opt for ACLED over the Uppsala Conflict Data Program’s Geo-referenced Event Data (UCDP-GED). UCDP-GED only includes incidents that result in at least one direct death. We validate this choice using the Energy Infrastructure Attack Database (EIAD), which expands the Global Terrorism Database to include non-state violence directed at energy infrastructure between 1980–2013 (Giroux et al. 2013). While ACLED and EIAD include different types of events and rely on different sources and geocoding methods, we find that ACLED better overlaps with EIAD than UCDP-GED. In grid cell-years in which the EIAD records an attack or attempted attack on an oil or gas pipeline or terminal, the probability that ACLED also codes an attack is roughly five times higher than UCDP-GED. UCDP-GED does not record a single conflict in any observation in which the EIAD records an attack on an oil or gas terminal.²¹

We do not use the EIAD in our primary analysis, as our main result would be mechanical: attacks on oil and gas infrastructure can only increase in locations where such infrastructure is built. Nonetheless, the EIAD confirms the part of Hypothesis H1 comparing attack risks of different types of infrastructure. Specifically, in Africa between 1997 and 2013 it records over eight times more incidents related to pipelines than oil terminals. Giroux et al. (2013: 124) also observe this pattern in the global EIAD sample and write, “attacks predominantly take place on ‘linear’ energy infrastructures (e.g., pipelines and transmission lines) that are difficult to protect and often pass through remote areas.” Furthermore, we show that our analyses for Hypotheses H2 and H3 deliver qualitatively similar results when we use the EIAD to measure conflict.

3.4 Units of analysis

Appendix Section F.2 illustrates how we construct our grid cell-by-year panel. For a given year, we map both infrastructure and conflict, and Appendix Figure A.3 uses 2001 and 2015 as examples. We then overlay equally sized grid cells and determine whether a particular type of infrastructure or conflict falls within each grid cell in that year. (Our actual panel uses 5 km × 5 km grid cells.) This results in tabular, grid cell-by-year data, as in the tables in the bottom of Appendix Figure A.3. Expanding this procedure to cover the whole region and all years, we generate our balanced panel of 1,474,363 grid cells over 18 years.

Many papers use a gridded dataset provided by PRIO, which uses grid cells that are 55 km × 55 km. We opt for a smaller grid for two reasons. First, we can more confidently attribute violence

21. In the EIAD, we classify oil and gas command and control centers, pumping stations, refineries and processing plants, and storage facilities as terminals.

to oil infrastructure if the incidents occur close to those features.²² Second, we are interested in whether armed groups appear to change the sites of their attacks. A PRIO grid cell is 3,025 sq. km. If violence occurs at two sites separated by over 50 kilometers (hours of travel time in remote settings), we do not want to code those attacks as occurring in the same location. It is important to note that partitioning the grid more finely reduces the baseline probability of violence: the likelihood of conflict in any given year in a specific 25 sq. km area is, unsurprisingly, quite low. As with the PRIO grid, we spatially merge in other covariates and include time-varying measures of population and luminosity. The latter is a common proxy for economic development.²³

4. Empirical Strategy and Results

We use different empirical strategies to assess our hypotheses (H1–H3). In the sections that follow, we introduce these strategies and discuss the associated results.

4.1 Armed Conflict Concentrates Along Pipelines (H1)

Our first hypothesis is that the presence of pipelines increases the probability of armed conflict, and that this effect exceeds any increase induced by other more critical oil infrastructure. Starting with descriptive statistics, Table 1 shows the percentage of observations experiencing different types of armed conflict (e.g., any ACLED event, any battle) when different types of infrastructure are present or absent. We differentiate two types of control observations: those from cells that never contain a particular type of infrastructure (“never treated”), and those from cells that will eventually contain such infrastructure (“not yet treated”). Looking at the first row of Table 1, a battle occurs in only 0.03 percent of observations from cells that never contain an oil or gas pipeline. This is higher (0.06) for control observations in cells that will eventually contain a pipeline, but still considerably lower than the likelihood in cell-years with an oil and gas pipeline (0.16). Across all of our conflict variables, the probability of violence is two or more times as large in cell-years with pipelines than those without. The same pattern does not hold for other infrastructure: the probability of violence is lower in cell-years with an active wellhead, as is the probability of a battle in cell-years with an oil or gas terminal.

To account for confounds that could affect both the siting of infrastructure and occurrence of violence (e.g., terrain, government turnover), we estimate the following two-way fixed effects (TWFE) model:

22. We do not, however, want to opt for too high of a resolution: given some imprecision in the geo-coding of features and conflict, we risk dissociating oil-related conflicts from associated infrastructure if partition the map too finely.

23. We use population data from the LandScan (Bright and Coleman 2001) and Gridded Population of the World (version 4) datasets (Center for International Earth Science Information Network 2018). These data provide measures for each raster cell in 1990, 2000, 2005, 2010, and 2015; we linearly interpolate to construct an annual measure. We use annual luminosity data from NOAA’s DMSP-OLS for 1996–2012 and then aggregate monthly data from VIIRS-DNB for 2013–2014.

Table 1: Oil and Gas Infrastructure and Armed Conflict

	ACLED Event	Battle	Rebel Battle	Eth. Militia Battle	Cell-Years
Pipelines					
Never treated	0.08	0.03	0.02	0.01	26,310,150
Not yet treated	0.23	0.06	0.02	0.01	35,327
Treated	0.45	0.16	0.06	0.03	193,057
Fields					
Never treated	0.08	0.03	0.02	0.01	26,429,688
Not yet treated	0.10	0.02	0.01	0.02	9,315
Treated	0.15	0.06	0.01	0.01	99,531
Wells					
Never treated	0.08	0.03	0.02	0.01	26,513,154
Not yet treated	0.08	0.03	0.01	0.01	23,542
Treated	0.00	0.00	0.00	0.00	1,838
Terminals					
Never treated	0.08	0.03	0.02	0.01	26,537,904
Not yet treated	0.61	0.61	0.61	0.00	164
Treated	2.79	0.43	0.21	0.00	466

Table 1: “Never treated” are cells that never receive oil infrastructure by type; “not yet treated” cell-years that later receive it but have not yet; and “treated” cell-years with oil infrastructure currently. We calculate the proportion of cell-years experiencing each type of conflict and multiply by 100.

$$y_{ict} = \alpha_i + \delta_{ct} + \beta_1 \mathbb{1}(\text{Pipeline})_{it} + \beta_2 \mathbb{1}(\text{Field|Well|Terminal})_{it} + \psi X_{it} + \varepsilon_{ict} \quad (1)$$

where i indexes grid cells, c countries, and t years. These models include a fixed effect for every grid cell (α_i) and for every country-year (δ_{ct}), as well as indicators for whether a pipeline or other type of infrastructure is present. In robustness checks, we include time-varying covariates for population and luminosity in X_{it} (see Appendix Table 5). We cluster our standard errors on grid cell and show robustness to clustering on larger spatial units in Appendix Table A.2.²⁴

H1 states that pipelines generate a larger increase in the probability of violence than other types of infrastructure (i.e., β_1 exceeds β_2). This is what we find across all models in Table 2: we can reject the null hypothesis that the coefficients are equal. Pipelines increase the likelihood of violence, whereas other types of infrastructure generate null or negative effects. The effects of pipeline construction are positive, significant at convention levels, and large relative to the levels of violence observed prior to pipelines coming online. Looking at model 2, the effect of a pipeline is more than double the base rate of 0.06. In Appendix Figure 1, we show that the results in

24. To allay concerns about spatial spillovers — namely, that infrastructure does not increase conflict but merely “attracts” violence that would have otherwise occurred in nearby control areas — we drop all never-treated cells that are adjacent to cells with infrastructure. The coefficients in Appendix Table 6 do not increase, suggesting that such spillovers do not meaningfully inflate our estimates.

model 2 are robust to dropping observations from any country in the sample. Our point estimates and inferences are also similar if we use larger 10x10-km grid cells as our units of analysis (see Appendix Table A.3).

Table 2: Effect of New Infrastructure on Armed Conflict

	ACLED Event	Battle	Rebel Battle	Rebel or Eth. Militia Battle
Pipeline ($\hat{\beta}_1$)	0.256*** (0.052)	0.171*** (0.039)	0.036** (0.016)	0.086*** (0.026)
Field, Well or Terminal ($\hat{\beta}_2$)	0.034 (0.052)	0.025 (0.037)	-0.019* (0.011)	-0.027* (0.015)
Equiv. Test ($H_0 : \beta_1 = \beta_2$)	0.00	0.01	0.01	0.00
Cells	1,474,363	1,474,363	1,474,363	1,474,363
Country-Years	869	869	869	869
N	26,538,534	26,538,534	26,538,534	26,538,534

Table 2 presents the main results assessing the effect of construction of a new pipeline ($\hat{\beta}_1$), a new field, well or terminal ($\hat{\beta}_2$), as well as the p-value from an equivalence test of the difference between the two coefficients ($H_0 : \hat{\beta}_1 = \hat{\beta}_2$). Models are estimated using OLS with cell and country-by-year fixed effects, with standard errors clustered on cell. We report the number of cells and country-years in the analysis as well as the total sample size. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

We invoke the standard parallel trends assumption and bolster this in four ways. First, we control for two potential time-varying confounds, population and economic development (Appendix Table 5). Our point estimates and inferences are unchanged. Second, we conduct placebo tests by dropping all post-treatment data and recoding treatment as the five years prior to infrastructure coming online. In Appendix Table A.4, we cannot reject the null hypothesis of no effect for these placebo treatments across all models.²⁵ Third, our event-study plots (Appendix Figure 2) reveal that, before treatment, we do not observe divergent changes in violence in treatment and control cells (see also the dynamic effect estimates in Appendix Figure A.4). Fourth, we focus on the “triple difference,” that is, whether the effect of new pipelines exceeds the effects of other types of infrastructure. If governments or companies locate infrastructure in areas with rising violence or if new infrastructure induces similar time-varying changes, such bias would shift both coefficients without necessarily affecting their difference. Furthermore, the triple-difference also alleviates concerns about reporting bias. Attacks on critical infrastructure are more unusual and occur in more populous areas than attacks on pipelines. As such, they are more likely to be cov-

25. The negative point estimates suggest that infrastructure is sited in cells with decreasing violence, an unsurprising form of selection bias that would attenuate the positive effects of pipelines.

ered by media and included in the ACLED data. This relative over-reporting of attacks on critical infrastructure would attenuate our triple-difference (by increasing $\hat{\beta}_2$).

An alternative explanation arises from confounding due to road construction: access roads are sometimes built alongside infrastructure, making it easier for groups to attack certain areas. This effect should be stronger for pipelines that traverse more remote areas than for infrastructure that might be built in already accessible areas. To rule out this alternative explanation, we use digitized road maps of Africa compiled by the Michelin Tire Company to code whether roads were present in a cell in 1990. In Appendix Table 7, we estimate a TWFE model (similar to Equation 1) that includes our measures of new infrastructure and their interaction with an indicator for road presence in 1990.²⁶ We find that the conflict-enhancing effects of pipelines on conflict are primarily driven by the construction of pipelines in cells that already contained roads in 1990; they are not driven by the construction of pipelines in cells containing no roads where simultaneous road construction might be confounding.

We also show that the conflict-enhancing effect of new pipelines is not confined to areas with historically marginalized groups.²⁷ Using the Ethnic Power Relations dataset (Wucherpfennig et al. 2011), we identify areas inhabited by ethnic or religious groups which were discriminated against or espoused separatist demands in the decade prior to our study period (1987–1996). We find that the effect of new pipelines on armed conflict is not significantly greater in such areas (see Appendix Table A.5), suggesting that our results are not the product of pre-existing (political) grievances and oil infrastructure.

Finally, in settings like ours where treatment timing varies, recent work shows that TWFE models assume negligible treatment effect heterogeneity. In Appendix Section G.5 we employ the diagnostics and alternative estimation strategies developed by De Chaisemartin and d’Haultfoeuille (2020), Goodman-Bacon (2021), and Callaway and Sant’Anna (2020) to assess the effect of new pipelines on armed conflict. In particular, Goodman-Bacon’s (2018) decomposition illustrates why the pathologies of TWFE models are unlikely to manifest in our setting. With a large number of never-treated cells in our data, over 99 percent of the weight in our TWFE model is placed on comparisons of treated vs. never-treated cells (see Appendix Table A.6). Our results do not depend on comparisons of early-treated (or always-treated) vs. later-treated cells, which can be problematic if treatment effects vary over time.

4.2 Attackers Vary their Points of Attack (H2)

Our second hypothesis is that past attacks should not predict what segments of pipeline are subsequently sabotaged. Armed groups increase their chances of success by deliberately randomizing

26. We also include a measure of luminosity (and its interactions with our infrastructure variables) to control for development, which might also be correlated with road access and conflict.

27. For a review of work relating grievances and conflict, see Cederman and Vogt (2017).

their attacks. In contrast, if these armed groups concentrate on certain segments, then the government could redeploy its defensive resources and thwart attacks. To assess this, we look at whether past attacks predict future attacks, expecting there to be little positive autocorrelation in attack locations. A positive autocorrelation could emerge, for example, if armed groups learned about and repeatedly attacked vulnerable sites. We restrict attention to grid cells with oil or gas pipelines throughout the study period and study whether past conflict (over the prior two or three years) predicts where battles occur, estimating:

$$y_{ict} = \alpha_i + \delta_{ct} + \sum_{k=1}^K \lambda_k y_{i,t-k} + \varepsilon_{ict} \quad (2)$$

We present two quantities to summarize our findings. First, we sum the coefficients on the lags (a la Bazzi and Blattman 2014).²⁸ Second, we use the Yule-Walker equations to estimate the autocorrelation ρ_k at lag k , which is the correlation between y_t and y_{t-k} . In both cases, we use the delta method to compute the standard errors. Appendix Tables 8 and 9 separately report the coefficients on the lags.²⁹ The null hypothesis — which is consistent with our theoretical prediction — is that past armed conflict incidence does not predict what cells with pipelines will see subsequent attacks.³⁰ We expect the sum of the autoregressive coefficients to be small and the autocorrelations to be negligible.

Our results align with the predictions of our Blotto game. Past armed conflict (over the last two to three years) does not predict where battles occur along pipelines. Looking at the sum of the coefficients, we cannot reject the null hypothesis in the first three columns for either the AR(2) or AR(3) models. To help benchmark these results, we estimate the same models using the occurrence of a protest or riot as the outcome measure: the sum of the coefficients from the AR(2) and AR(3) models are 0.3 and highly significant. A similar pattern emerges when we look at the autocorrelations. The autocorrelations for battles, particularly those involving rebels or ethnic militias, are small in magnitude and quickly converge to zero. This is also true if we code attacks using the EIAD, which narrowly focuses on direct attacks on energy infrastructure like pipelines (Appendix Tables A.7 and A.8). Again, this contrasts with social conflicts, for which the

28. Andrews and Chen (1994) illustrate the relationship between the cumulative impulse response function and the sum of autoregressive coefficients, arguing that the latter provides a good scalar measure of persistence.

29. In column 1 of Appendix Tables 8 and 9 the first lag of battles is positive and statistically significant $\hat{\lambda}_1 = 0.1$. That coefficient attenuates to zero and loses significance when we restrict attention to battles involving rebels and ethnic militias (columns 2–3). The significant coefficient appears to be driven by battles involving political militias, which are “not seeking the removal of a national power, but typically supported by, armed by, or allied with a political elite” (Raleigh et al. 2017: 17). These militias — which are a different category than ethnic militias — are often allied with the government and do not need to evade its defenses as in our Blotto model. When we remove battles involving political militias, the coefficient on the first lag attenuates and loses significance.

30. We condition on country-year and cell fixed effects. In reality, some segments of pipelines may be infeasible to attack (e.g., deep underwater). The cell fixed effects help account for (unmodeled) variation that may reduce the baseline vulnerability of some segments.

Table 3: Predictive Power of Past Armed Conflict

	Battle	Rebel Battle	Rebel or Eth. Militia Battle	Protest or Riot
AR(2) Model:				
Sum of Coefficients: $\hat{\lambda}_1 + \hat{\lambda}_2$	0.067 (0.053)	-0.004 (0.059)	-0.018 (0.051)	0.312 (0.045)
Autocorrelations				
$\hat{\rho}_1$	0.107 (0.030)	0.056 (0.041)	0.031 (0.032)	0.234 (0.036)
$\hat{\rho}_2$	-0.033 (0.038)	-0.061 (0.034)	-0.05 (0.030)	0.15 (0.035)
$\hat{\rho}_3$	-0.009 (0.007)	-0.007 (0.005)	-0.003 (0.003)	0.055 (0.019)
Cells	8,172	8,172	8,172	8,172
Country-Years	240	240	240	240
N	130,752	130,752	130,752	130,752
AR(3) Model:				
Sum of Coefficients: $\hat{\lambda}_1 + \hat{\lambda}_2 + \hat{\lambda}_3$	0.075 (0.072)	-0.028 (0.066)	-0.054 (0.055)	0.318 (0.060)
Autocorrelations				
$\hat{\rho}_1$	0.096 (0.031)	0.044 (0.039)	0.019 (0.031)	0.221 (0.037)
$\hat{\rho}_2$	-0.038 (0.040)	-0.06 (0.041)	-0.051 (0.033)	0.135 (0.038)
$\hat{\rho}_3$	0.012 (0.032)	-0.017 (0.041)	-0.022 (0.035)	0.08 (0.042)
Cells	8,859	8,172	8,172	8,172
Country-Years	225	225	225	225
N	122,580	122,580	122,580	122,580

Table 3 summarizes estimates from a two-period auto-regressive model (AR(2) in top panel) and a three-period model (AR(3) in bottom panel). The outcome of each regression is the contemporaneous indicator for whether an attack took place and the predictors are the lagged outcomes in the same cell. Models are estimated using OLS with cell and country-by-year fixed effects, with standard errors clustered on cell. We report (1) the sum of the lags and (2) the autocorrelations derived using the Yule-Walker equations. We include standard errors computed using the delta method. We report the number of cells and country-years in the analysis as well as the total sample size.

autocorrelation remains positive and of a larger magnitude. These differences are particularly stark given that event datasets using media and NGO sources, such as ACLED, tend to measure non-violent events like protests with greater error than violent events like battles (Demarest and Langer 2018; Day et al. 2015). As such, we expect the estimates in Table 3 to understate the autocorrelation in protests and riots. Overall, knowing the locations of recent protests or riots is informative about where subsequent social conflict will occur, but the same is not true of armed conflict along pipelines. This is consistent with attackers intentionally randomizing across potential pipeline segments to avoid confrontations with security forces.

4.3 Black-market and Export Prices Have Different Effects (H3)

Our third hypothesis predicts that increases in the rebel's value of oil should have stronger conflict-enhancing effects than increases in the government's value of oil. As described, we use the local

fuel price as a proxy for the value of stolen oil to non-state armed groups (v^A). The global price measures the value of oil to the government (v^G). Interacting both prices with an indicator for cells containing oil pipelines permits us to assess our model’s prediction that the effects of local prices exceed the violence-inducing effects of global prices. We restrict attention to grid cells with no change in oil infrastructure between 2003 and 2014, which is the study period for this analysis due to data constraints.³¹

Specifically, we estimate:

$$y_{ict} = \alpha_i + \delta_{ct} + \gamma_1 \text{Log(Local)}_{ct} \cdot \mathbb{1}(\text{Pipeline})_i + \gamma_2 \text{Log(Global)}_t \cdot \mathbb{1}(\text{Pipeline})_i + \zeta Z_{it} + \epsilon_{ict} \quad (3)$$

where the cell fixed effects (α_i) absorb the direct effect of having a pipeline throughout the study period, and the country-by-year fixed effects (δ_{ct}) absorb the direct effects of price fluctuations. Although previous work documents that the gap between local and global gasoline prices is driven by macro-level factors such as inflation and oil prices (Ross et al. 2017) or “idiosyncratic, evanescent, country-specific factors” (Mahdavi et al. 2022: 2137), local prices might be driven by violence. To alleviate concerns about reverse causality, we regress the local gasoline price on a country-year measure of violence — namely, the number of grid cells (logged) with a conflict in the previous year. Appendix Table 10 shows negligible and insignificant effects of conflict on local gas prices.

Table 4: Effect of Fuel Prices on Armed Conflict near Existing Infrastructure

	Battle	Rebel Battle	Rebel or Eth. Militia Battle
Log(Local Price) x Pipeline (γ_1)	0.065 (0.113)	0.110* (0.061)	0.106 (0.066)
Log(Global Price) x Pipeline (γ_2)	0.008 (0.083)	-0.117** (0.057)	-0.108* (0.060)
Equivalence Test ($H_0 : \gamma_1 = \gamma_2$)	0.76	0.05	0.07
Cells	1,464,041	1,464,041	1,464,041
Country-Years	536	536	536
N	17,216,229	17,216,229	17,216,229

Table 4 shows the effect of (log) changes in the local price of gasoline in places with pipelines ($\hat{\gamma}_1$) and of (log) changes in the global price of gas in places with pipelines ($\hat{\gamma}_2$), as well as a p-value for the equivalence test of difference between the two ($H_0 : \gamma_1 = \gamma_2$). Prices are interacted with indicators for the presence of each type of infrastructure throughout the time series, and therefore the estimates represent conditional effects of price changes on the probability of experiencing a conflict event among cells with pipelines. Models are estimated using OLS with cell and country-by-year fixed effects, with standard errors clustered on cell. We report the number of cells and country-years in the analysis as well as the total sample size. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

31. We are not estimating the total effect of oil prices on conflict: by focusing on cells with no new infrastructure, we exclude the possibility that conflict causes the construction of new infrastructure.

Models 2 and 3 of Table 4 are consistent with our theoretical predictions. Increases to the local price of fuel have a larger effect on battles involving rebels and militia along pipelines than increases to the global price. We can reject the null hypothesis that these different prices have the same effect at conventional levels of statistical significance, and these p -values decline further if we perform the one-sided test implied by our model. Holding the local price constant, we estimate that increases to the global price actually reduce the likelihood of violence. Relating this back to our theory, as the government's value of oil increases, it increases its offer to armed groups, and this can reduce the probability of subsequent violence.

Appendix Table A.9 shows minimal increases in our standard errors when we cluster on larger geographies. Moreover, our point estimates and inferences are similar if we use larger 10x10-km grid cells as our units of analysis (see Appendix Table A.10). Appendix Table 11 also shows that point estimates and inferences are unaffected by including time-varying controls for population and luminosity. Finally, Appendix Table A.11 shows that our results are qualitatively similar if we use the EIAD to code attacks or, more specifically, attacks on oil infrastructure: increases in the the local price exacerbates conflict, and we can reject the null that the local and global prices have equivalent effects.

5. Policy Implications

Our analysis clarifies potential tradeoffs between promoting security and economic development. Suppose the goal is to reduce sabotage and promote security. One obvious approach is to physically secure pipelines. Yet, deterring attacks can also restrain economic well-being. In contexts where armed groups and the communities they draw from need to flex to garner concessions from government, discouraging violence may not improve welfare (Wick and Bulte 2006). Policies that raise the cost of attacks eliminate a “weapon of the weak.” Thus, the set of groups that can credibly threaten violence is restricted, reducing both the frequency and scale of payouts. Where government cannot commit to payouts for aggrieved groups, violence provides an accountability mechanism, albeit a mechanism divorced from need which generates social and environmental externalities. As Levi (1988: 12) observes, “since bargaining resources are distributed unequally throughout the population, a single ruler will form different contracts with different groups of agents or constituents.”

Suppose instead that the goal is to promote economic development. We could, for example, require oil producers to clean up the spills caused by pipeline sabotage. To avoid that expense, they would be keen to bargain with potential attackers and offer larger payouts. More generous payouts and environmental reclamation could benefit communities in oil-producing regions. But the policy could also encourage attacks. The promise of bigger payouts induces a larger share of groups to attack, hoping to secure a seat at the bargaining table. There is some evidence of this

in Nigeria where the distribution of amnesty payments was followed by pipeline sabotage by new armed groups. One group actually called itself “Third Wave Federal Amnesty,” referring to its goal of being included in a future wave of government payouts (Eke 2015: 758). A policy that advances economic development by increasing payouts to aggrieved groups could undermine security by generating perverse signaling incentives that provoke violence. Promoting both peace and economic development requires a more accountable state, a setting in which groups and communities do not need to take up arms to see their needs addressed. A responsive state could then repress violence without also hampering development.

Finally, our analysis suggests a new avenue through which fossil-fuel subsidies can encourage peace. Past scholarship argues that, by reducing energy prices, fuel subsidies prevent urban riots and protests (Bates 1981; Kim and Urpelainen 2016). Fossil fuel subsidies also have spillover effects by depressing demand for illegally refined oil. This reduced demand decreases the expected benefits from oil theft, decreasing the likelihood of attacks. Our research suggests that subsidies also discourage armed conflict around pipelines crisscrossing more rural areas, a claim consistent with recent analyses of pipeline sabotage and oil theft in Mexico (International Crisis Group 2022).

6. Conclusion

We develop a model that integrates common approaches to modeling conflict including crisis bargaining with incomplete information and Blotto-style contests with multiple battlefields. We use geo-spatial data on the location of oil infrastructure and armed conflict events to assess several of the model’s observable implications.

First, we predict and show empirically that armed groups focus their attacks on new pipelines and that the construction of more critical infrastructure (e.g., oil wells and terminals) has no discernible effect on armed conflict. Armed groups anticipate that the government will station its defenses around critical infrastructure (i.e., the largest prizes), so they attack pipelines, which are softer targets, instead. Second, to prevent the government from forecasting and preventing their attacks, armed groups randomize where they strike. We find that past attacks (over the last two or three years) do not predict which sections of pipeline will be subsequently sabotage. This contrasts sharply with social conflict events (e.g., protests), which we show tend to recur in the same locations year after year. Third, the model uncovers two potentially offsetting effects of increased oil prices. As the black-market price increases, so too do the returns to oil theft; yet as the export price increases, the government is more eager to “bargain away” conflict. We find empirical support for these predictions, showing significantly different effects of increases in the local price of gasoline (which establishes a ceiling on the local black-market price) and the global price of gasoline (which reflects its export value).

These findings contribute to our understanding of where and why armed conflict occurs. While armed groups want to capture prized targets, they also prioritize success and will therefore attack peripheral targets to elude the government's defenses. Our model explains where violence will occur by forcing armed groups to consider both the size of the potential prize and also their ability to evade strategically positioned security forces. We also argue that, even with instances of oil theft, attacks on pipelines are not entirely attributable to greed. Armed groups and the communities they draw from often have grievances related to economic, environmental, or political inequality. Sabotaging pipelines can send a costly signal of a group's capacity to credibly threaten the government, and doing so compels the government to grant concessions. Greed and grievance can be complementary explanations for conflict: if a group profits from pilfering oil (greed), then government needs to seriously engage with its demands (grievance) to deter violence.

Several limitations of our work might be addressed in future research. Theoretically, we assume that armed groups' strength is uniformly distributed and focus on observable implications that do not turn on this auxiliary assumption. Future work might exploit case knowledge to assert a more realistic distribution. For example, if weaker groups are more likely than stronger groups, then policies encouraging larger government payoffs will increase the expected number of attacks because the signaling incentive for weaker groups overwhelms the pacifying effect of payouts on stronger ones. Empirically, data limitations might be overcome in future work. We have general descriptions of well-fortified oil terminals but lack detailed data on the deployment of security forces. We also rely on a proxy for black-market fuel prices; measuring black-market prices more directly would incorporate international demand for stolen oil. Finally, we study one important sector, but other supply chains may face similar threats. International Alert (2005: 132), for example, observes that projects which rely on "linear components" such as transmission lines or transportation bottlenecks are especially vulnerable to disruption. Future research will reveal whether the patterns we uncover manifest in other sectors.

References

- Adibe, Raymond, Ejikeme Nwagwu, and Okorie Albert. 2018. "Rentierism and security privatisation in the Nigerian petroleum industry." *Review of African Political Economy* 45 (156): 345–353.
- Amaize, Emma, and Sam Oyadongha. 2008. "Militants Agree to Cease-Fire!" *Vanguard* 21 September.
- Amunwa, Ben. 2012. "Dirty Work." *Platform Technical Report*, 1–14.
- Andersen, Jorgen Juel, Frode Nordvik, and Andrea Tesei. 2022. "Oil price shocks and conflict escalation." *Journal of Conflict Resolution* 66 (2): 327–356.
- Andrews, Donald WK, and Hong-Yuan Chen. 1994. "Approximately median-unbiased estimation of autoregressive models." *Journal of Business & Economic Statistics* 12 (2): 187–204.

- Asal, Victor, Michael Findley, James A Piazza, and James Igoe Walsh. 2016. "Political exclusion, oil, and ethnic armed conflict." *Journal of Conflict Resolution* 60 (8): 1343–1367.
- Asuni, Judith Burdin. 2009. "Understanding the Armed Groups of the Niger Delta." *CFR Working Paper*, 1–31.
- Bates, Robert, Avner Greif, and Smita Singh. 2002. "Organizing violence." *Journal of Conflict Resolution* 46 (5): 599–628.
- Bates, Robert H. 1981. *Markets and States in Tropical Africa*. UC Press.
- Bazzi, Samuel, and Christopher Blattman. 2014. "Economic shocks and conflict: Evidence from commodity prices." *AEJ: Macroeconomics* 6 (4): 1–38.
- Besley, Timothy, and Torsten Persson. 2011. "The Logic of Political Violence." *The Quarterly Journal of Economics* 126, no. 3 (August): 1411–1445.
- Blair, Graeme, Darin Christensen, and Aaron Rudkin. 2021. "Do Commodity Price Shocks Cause Armed Conflict?" *American Political Science Review*.
- Bright, Eddie A., and Phil R. Coleman. 2001. "LandScan."
- Callaway, Brantly, and Pedro HC Sant'Anna. 2020. "Difference-in-Differences with multiple time periods." *Journal of Econometrics*.
- Cederman, Lars-Erik, and Manuel Vogt. 2017. "Dynamics and logics of civil war." *Journal of Conflict Resolution* 61 (9): 1992–2016.
- Center for International Earth Science Information Network. 2018. "Gridded Population of the World, Version 4: Population Count."
- Collier, Paul, and Anke Hoeffler. 1998. "On economic causes of civil war." *Oxford Econ. Papers* 50 (4): 563–573.
- . 2004. "Greed and grievance in civil war." *Oxford Econ. Papers* 56 (4): 563–595.
- Cotet, Anca M, and Kevin K Tsui. 2013. "Oil and conflict: What does the cross country evidence really show?" *AEJ: Macroeconomics* 5 (1): 49–80.
- Dal Bó, Ernesto, and Pedro Dal Bó. 2011. "Workers, Warriors, and Criminals: Social Conflict in General Equilibrium." *Journal of the European Economic Association* 9 (4): 646–677.
- Day, Joel, Jonathan Pinckney, and Erica Chenoweth. 2015. "Collecting data on nonviolent action." *Journal of Peace Research* 52 (1): 129–133.
- De Chaisemartin, Clément, and Xavier d'Haultfoeuille. 2020. "Two-way fixed effects estimators with heterogeneous treatment effects." *American Economic Review* 110 (9): 2964–2996.
- De Soysa, Indra. 2002. "Paradise is a bazaar? Greed, creed, and governance in civil war, 1989-99." *Journal of Peace Research* 39 (4): 395–416.
- De Soysa, Indra, and Eric Neumayer. 2007. "Resource Wealth and the Risk of Civil War Onset." *Conflict Management and Peace Science* 24 (3): 201–218.
- Dechenaux, Emmanuel, Dan Kovenock, and Roman M Sheremeta. 2015. "A survey of experimental research on contests, all-pay auctions and tournaments." *Experimental Economics* 18 (4): 609–669.
- Demarest, Leila, and Arnim Langer. 2018. "Violence and social unrest in Africa." *African Affairs* 117 (467): 310–325.
- Denly, Michael, Michael Findley, Joelean Hall, Andrew Stravers, and James Igoe Walsh. n.d. "Do Natural Resources Really Cause Civil Conflict." *Journal of Conflict Resolution*.

- Dube, Oeindrila, and Juan F. Vargas. 2013. "Commodity price shocks and civil conflict." *The Review of Economic Studies* 80 (4): 1384–1421.
- Eke, Surulola James. 2015. "No pay, no peace." *Journal of Asian and African Studies* 50 (6): 750–764.
- Fearon, James. 1995. "Rationalist explanations for war." *International Organization* 49:379–414.
- . 2005. "Primary commodity exports and civil war." *Journal of Conflict Resolution* 49 (4): 483–507.
- Fearon, James, and David Laitin. 2003. "Ethnicity, Insurgency, and Civil War." *American Political Science Review* 101 (1): 75–90.
- Garfinkel, Michelle R., and Stergios Skaperdas. 2007. "Economics of Conflict." In *Handbook of Defense Economics*, edited by Todd Sandler and Keith Hartley, 2:649–709. Elsevier.
- Giroux, Jennifer, Peter Burgherr, and Laura Melkunaite. 2013. "The Energy Infrastructure Attack Database." *Perspectives on Terrorism* 7 (6): 113–125.
- Glynn, Adam. 2009. "Does oil cause civil war because it causes state weakness?"
- Goodman-Bacon, Andrew. 2021. "Difference-in-differences with variation in treatment timing." *Journal of Econometrics*.
- Grossman, Herschel. 1995. "Insurrections." In *Handbook of defense economics*, edited by Hartley and Sandier, 191–212. Elsevier.
- Hart, Sergiu. 2008. "Discrete Colonel Blotto and General Lotto Games." *International Journal of Game Theory* 36 (3): 441–460.
- Hazen, Jennifer M., and Jonas Horner. 2007. "Small arms, armed violence, and insecurity in Nigeria." Small Arms Survey.
- Hoeffler, Anke. 2011. "'Greed' versus 'Grievance'." *Studies in Ethnicity and Nationalism* 11 (2): 274–284.
- Holt, Charles A., and Thomas R. Palfrey. 2022. "Bilateral Conflict."
- Humphreys, Macartan. 2005. "Natural resources, conflict, and conflict resolution: Uncovering the mechanisms." *Journal of Conflict Resolution* 49 (4): 508–537.
- Initiative, Nigeria Extractives Industry Transparency. 2021. "Nigeria profile."
- International Alert. 2005. "Conflict-Sensitive Business Practice."
- International Crisis Group. 2022. "Keeping Oil from the Fire: Tackling Mexico's Fuel Theft Racket." *Crisis Group Latin America Briefing* 25 March (46).
- Katsouris, C., and Aaron Sayne. 2013. "Nigeria's criminal crude." Chatham House.
- Kim, Sung Eun, and Johannes Urpelainen. 2016. "Democracy, autocracy and the urban bias." *Political Studies* 64 (3): 552–572.
- Kimbrough, Erik, Kevin Laughren, and Roman Sheremeta. 2020. "War and conflict in economics." *Journal of Economic Behavior & Organization* 178:998–1013.
- Kydd, Andrew H, and Barbara F Walter. 2006. "The strategies of terrorism." *International Security* 31 (1): 49–80.
- Lagos, U.S. Consulate. 2009. "Nigeria: Amnesty ends on a high note but what next?" Cablegate No. 09LAGOS375, September.
- Laitin, David D. 2007. *Nations, States, and Violence*. Oxford University Press.

- Lei, Yu-Hsiang, and Guy Michaels. 2014. "Do giant oilfield discoveries fuel internal armed conflicts?" *Journal of Development Economics* 110:139–157.
- Levi, Margaret. 1988. *Of Rule and Revenue*. University of California Press.
- Lujala, Päivi. 2010. "Spoils of nature." *Journal of Peace Research* 47 (1): 15–28.
- Mahdavi, Paasha, Cesar B. Martinez-Alvarez, and Michael L. Ross. 2022. "Why Do Governments Tax or Subsidize Fossil Fuels?" *Journal of Politics* 84 (4): 2123–2139.
- Massey, Simon, and Roy May. 2005. "Oil and Chad, external controls and internal politics." *Journal of Contemporary African Studies* 23 (2): 253–276.
- Morelli, Massimo, and Dominic Rohner. 2015. "Resource concentration and civil wars." *Journal of Development Economics* 117:32–47.
- Nellemann, Christian, Rune Henriksen, Riccardo Pravettoni, Davyth Stewart, Maria Kotsovou, M.A.J. Shlingemann, Mark Shaw, and Tuesday Reitano. 2018. "World Atlas of Illicit Flows." INTERPOL.
- Obi, Cyril. 2014. "Oil and the Post-Amnesty Programme (PAP)." *Review of African Political Economy* 41 (140): 249–263.
- Obi, Cyril, and Siri Aas Rustad. 2011. *Oil and Insurgency in the Niger Delta*. Zed.
- Onuoha, Freedom C. 2008. "Oil pipeline sabotage in Nigeria." *African Security Studies* 17 (3): 99–115.
- Oriola, Temitope, Kevin D Haggerty, and Andy W Knight. 2013. "Car Bombing 'With Due Respect'." *African Security* 6 (1): 67–96.
- Owen, Nick A, Oliver R Inderwildi, and David A King. 2010. "The status of conventional world oil reserves." *Energy Policy* 38 (8): 4743–4749.
- Oyadongha, Samuel. 2014. "We are committed to curbing crude oil theft in Niger Delta: JTF Commander." *This Day* 8 January.
- Paine, Jack. 2016. "Rethinking the conflict "resource curse"." *International Organization* 70 (4): 727–761.
- . 2019. "Economic grievances and civil war." *International Studies Quarterly* 63 (2): 244–258.
- Powell, Robert. 2007. "Defending against Terrorist Attacks with Limited Resources." *American Political Science Review* 101 (3): 527–541.
- Raleigh, Clionadh, A Linke, and Caitriona Dowd. 2017. "Armed Conflict Location and Event Data Project," 1–33.
- Raleigh, Clionadh, Andrew Linke, Havard Hegre, and Joakim Karlsen. 2010. "Introducing ACLED." *Journal of Peace Research* 47 (5): 651–660.
- Rexer, Jonah M, and Even C Hvinden. 2020. "Bargaining, war, and black market oil in Nigeria." Working Paper.
- Roberson, Brian. 2006. "The colonel blotto game." *Economic Theory* 29 (1): 1–24.
- Ross, Michael L. 2012. *The Oil Curse*. Princeton University Press.
- . 2015. "What Have We Learned about the Resource Curse?" *Annual Review of Political Science* 18 (1): 239–259.
- Ross, Michael L., Chad Hazlett, and Paasha Mahdavi. 2017. "Global progress and backsliding on gasoline taxes and subsidies." *Nature Energy* 2 (1): 1–6.

- Ross, Michael L., and Paasha Mahdavi. 2015. "Oil and Gas Data, 1932-2014."
- Scott, James C. 1985. *Weapons of the Weak*. Yale University Press.
- Sonin, Konstantin, and Austin L Wright. 2019. "Rebel capacity and combat tactics."
- Staff. 2009. "The Country's Oil Production Rises to 1.7 MBD." *Daily Trust* 27 Aug.
- Thomas, Jakana. 2014. "Rewarding bad behavior." *American Journal of Political Science* 58 (4): 804–818.
- Ukeje, Charles. 2001. "Youth, Violence and the Collapse of Public Order in the Niger Delta of Nigeria." *Africa Development* 26 (1): 337–366.
- Ukiwo, Ukoha. 2007. "Pirates to militants." *African Affairs* 106 (452): 587–610.
- USAID. 2006. "Democracy and governance assessment of Nigeria."
- VoA News. 2011. "Higher fuel taxes driving motorists to black market." 15 Jun.
- Walter, Barbara F. 2009. "Bargaining failures and civil war." *Annual Review of Political Science* 12:243–261.
- Watts, Michael, and S. Ibaba. 2011. "Turbulent oil." *African Security* 4 (1): 1–19.
- Wick, K., and E. Bulte. 2006. "Contesting resources." *Public Choice* 128:457–6.
- Wood, Elisabeth Jean. 2003. *Insurgent collective action and civil war in El Salvador*. Cambridge University Press.
- Wosu, Chinedu. 2008. "Militants blow up oil pipelines." *Daily Champion* 29 Jul.
- Wright, Joseph, Erica Frantz, and Barbara Geddes. 2015. "Oil and Autocratic Regime Survival." *British Journal of Political Science* 45 (2): 287–306.
- Wucherpfennig, Julian, Nils B. Weidmann, Luc Girardin, Lars-Erik Cederman, and Andreas Wimmer. 2011. "Politically relevant ethnic groups across space and time." *Conflict Management and Peace Science* 28 (5): 423–437.
- Zalik, Anna. 2011. "Labelling oil, contesting governance." In *Oil and insurgency in the Niger Delta*, edited by Cyril Obi and Siri Rustad, 184–199. Zed.

The Point of Attack: Where and Why Does Oil Cause Armed Conflict in Africa?

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Appendix

A. Effect of New Infrastructure

A.1 Leave-one-out Analysis

Figure 1: Leave-one-out Analysis of the Effects of Pipeline Construction

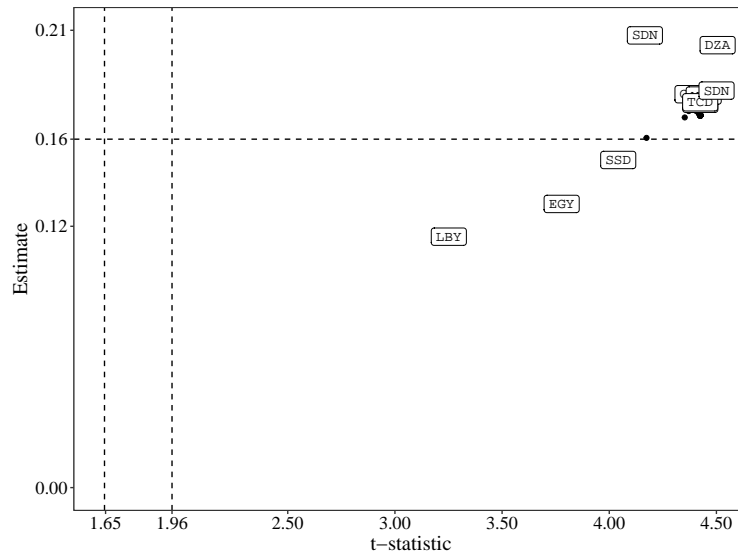


Figure 1 presents the results of reestimating model 2 of Table 2 after dropping a given country's data from the panel entirely. On the x-axis is the t-statistic, with the critical values of 1.65 (90% confidence) and 1.96 (95% confidence) noted in dashed lines. On the y-axis is the estimate, with the full sample estimate of 0.16 denoted by a dashed line. All results remain statistically significant and large.

A.2 Event Study Plots

Figure 2: Event-study Plots for Pipelines

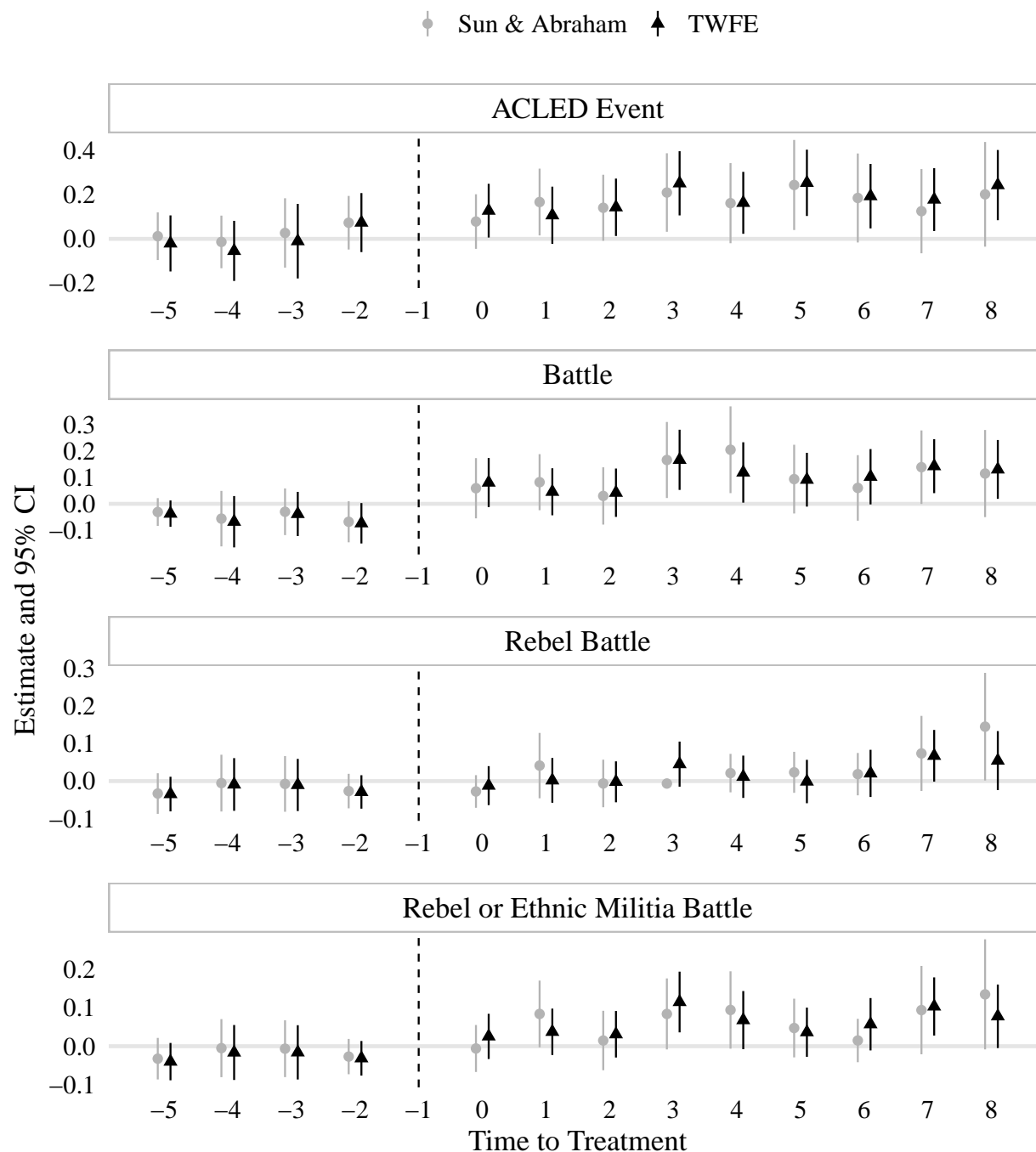


Figure 2 displays event-study plots for pipeline construction (controlling for new fields, wells, or terminals) using a two-way fixed effects model (black), as well as the approach proposed by Sun and Abraham (2021) (grey), which uses never-treated cells as the comparison group. To enable estimation using Sun & Abraham's approach, these figures use a sample that trims never-treated cells more than 50 kilometers from cells that ever contain infrastructure.

Figure 3: Event-study Plots for Fields, Wells, or Terminals

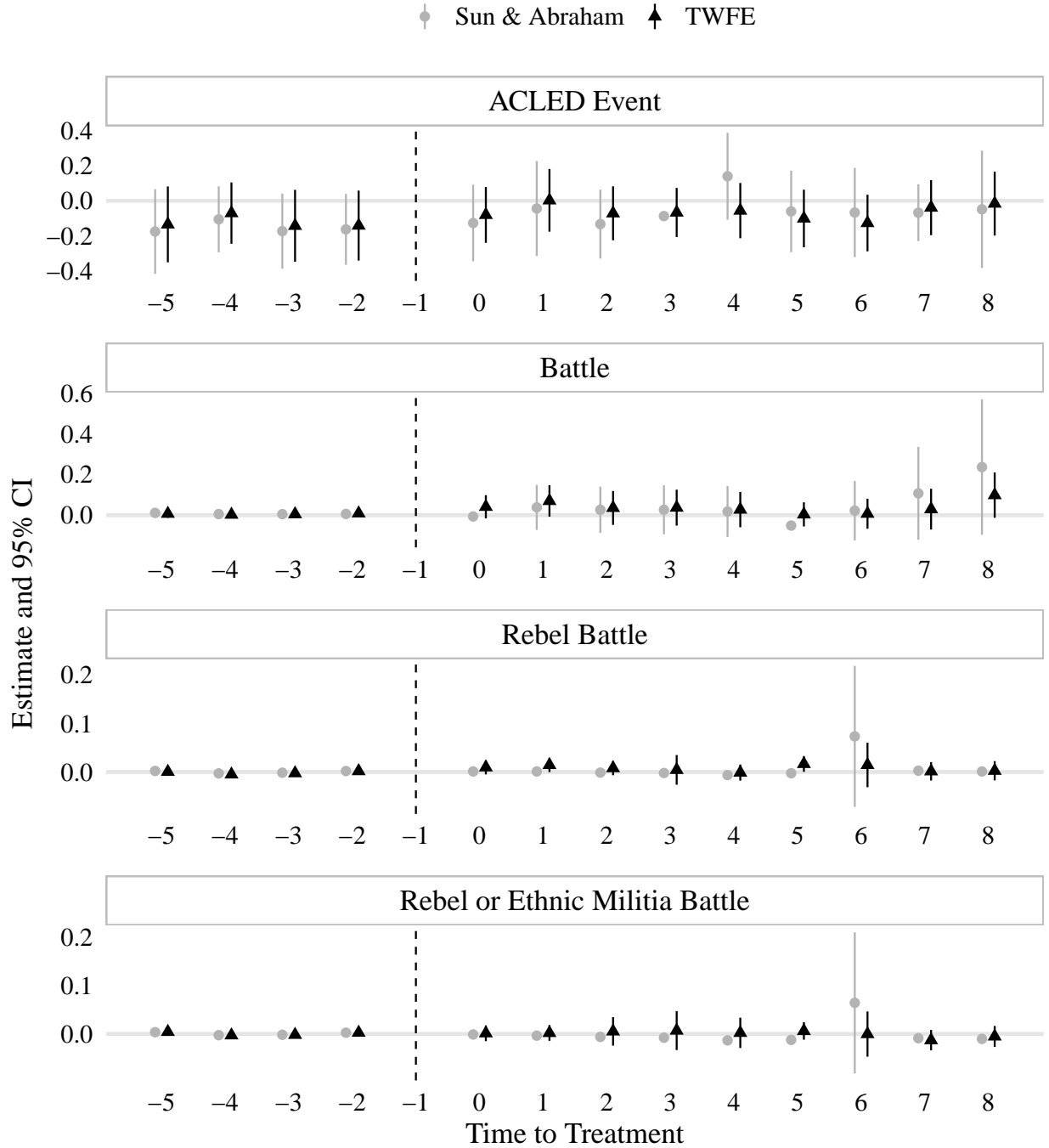


Figure 2 displays event-study plots for fields, wells, or terminals (controlling for pipelines) using a two-way fixed effects model (black), as well as the approach proposed by Sun and Abraham (2021) (grey), which uses never-treated cells as the comparison group. To enable estimation using Sun & Abraham's approach, these figures use a sample that trims never-treated cells more than 50 kilometers from cells that ever contain infrastructure.

A.3 Including Additional Time-varying Controls

Table 5: Effect of New Oil/Gas Infrastructure on Armed Conflict (with Controls)

	ACLED Event	Battle	Rebel Battle	Rebel or Eth. Militia Battle
Pipeline	0.257*** (0.052)	0.169*** (0.039)	0.037** (0.016)	0.087*** (0.026)
Field, Well or Terminal	0.022 (0.053)	0.022 (0.037)	-0.019* (0.011)	-0.027* (0.015)
Equivalence Test	0.00	0.01	0.00	0.00
Controls	✓	✓	✓	✓
Cells	1,474,360	1,474,360	1,474,360	1,474,360
Country-Years	869	869	869	869
N	26,405,190	26,405,190	26,405,190	26,405,190

Table 5 presents a reanalysis of Table 2 with added controls for (lagged) population and (lagged) night lights density, a measure of economic development. Models estimated using OLS with standard errors clustered at the grid cell level. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

A.4 Addressing spatial spillovers

Table 6: Effect of New Infrastructure on Armed Conflict Dropping Never-treated Cells Adjacent to Treated Cells

	ACLED Event	Battle	Rebel Battle	Rebel or Eth. Militia Battle
Pipeline ($\hat{\beta}_1$)	0.267*** (0.052)	0.174*** (0.039)	0.036** (0.016)	0.087*** (0.026)
Field, Well or Terminal ($\hat{\beta}_2$)	0.042 (0.052)	0.029 (0.037)	-0.018* (0.011)	-0.026* (0.015)
Equiv. Test ($H_0 : \beta_1 = \beta_2$)	0.00	0.01	0.01	0.00
Cells	1,380,631	1,380,631	1,380,631	1,380,631
Country-Years	869	869	869	869
N	24,851,358	24,851,358	24,851,358	24,851,358

Table 6 presents a reanalysis of Table 2 dropping never-treated cells that are adjacent to cells that ever contain infrastructure. Models estimated using OLS; standard errors clustered on grid cell. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

A.5 Moderation analysis

Table 7: Moderated Effect of Lagged Road Presence

	ACLED Event		Battle		Rebel Battle		Rebel or Eth. Militia Battle	
Pipeline	0.931*** (0.175)	0.777*** (0.156)	0.479*** (0.126)	0.389*** (0.112)	0.072 (0.047)	0.053 (0.042)	0.248*** (0.088)	0.207*** (0.078)
Field, Well or Terminal (FWT)	-0.283*** (0.109)	-0.281*** (0.106)	0.164 (0.213)	0.163 (0.210)	-0.069 (0.070)	-0.075 (0.069)	-0.091 (0.071)	-0.091 (0.069)
Pipeline x No Road in 1990	-0.696*** (0.156)	-0.732*** (0.160)	-0.287** (0.113)	-0.308*** (0.116)	-0.020 (0.043)	-0.025 (0.044)	-0.160** (0.078)	-0.170** (0.080)
FWT x No Road in 1990	0.369*** (0.123)	0.370*** (0.121)	-0.160 (0.209)	-0.161 (0.211)	0.069 (0.069)	0.066 (0.069)	0.076 (0.070)	0.076 (0.070)
No Nightlights	✓		✓		✓		✓	
No Nightlights x Pipeline	✓		✓		✓		✓	
No Nightlights x FWT	✓		✓		✓		✓	
Cells	1,474,363	1,474,363	1,474,363	1,474,363	1,474,363	1,474,363	1,474,363	1,474,363
Country-Years	869	869	869	869	869	869	869	869
N	26,538,534	26,538,534	26,538,534	26,538,534	26,538,534	26,538,534	26,538,534	26,538,534

Table 7 shows the effect of new pipeline construction moderated by whether roads were present in 1990 (all columns) and whether there the cell had any luminosity in the previous year (odd columns). The uninteracted variables for infrastructure in these latter models capture the effects of construction in cells that already had road access but no luminosity. Our measure of road access comes from digitized road maps of Africa compiled by the Michelin Tire Company. Models are estimated using OLS with cell and country-by-year fixed effects, with standard errors clustered on cell. We report the number of cells and country-years in the analysis as well as the total sample size. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

B. Autoregressive Models of Conflict Near Pipelines

B.1 Full models

Table 8: Predictive Power of Past Armed Conflict (AR(2) Model)

	Battle	Rebel Battle	Rebel or Eth. Militia Battle	Protest or Riot
t - 1	0.112 (0.030)	0.060 (0.043)	0.033 (0.034)	0.210 (0.030)
t - 2	-0.045 (0.036)	-0.064 (0.032)	-0.051 (0.029)	0.101 (0.029)
Sum of Coefficients	0.067 (0.053)	-0.004 (0.059)	-0.018 (0.051)	0.312 (0.045)
Cells	8,172	8,172	8,172	8,172
Country-Years	240	240	240	240
N	130,752	130,752	130,752	130,752

Table 8: presents the auto-regressive models summarized in Table 3. Standard errors are clustered on cell.

Table 9: Predictive Power of Past Armed Conflict (AR(3) Model)

	Battle	Rebel Battle	Rebel or Eth. Militia Battle	Protest or Riot
t - 1	0.101 (0.031)	0.046 (0.041)	0.019 (0.032)	0.197 (0.031)
t - 2	-0.046 (0.037)	-0.063 (0.039)	-0.052 (0.033)	0.086 (0.029)
t - 3	0.020 (0.030)	-0.011 (0.042)	-0.020 (0.035)	0.034 (0.034)
Sum of Coefficients	0.075 (0.072)	-0.028 (0.066)	-0.054 (0.055)	0.318 (0.06)
Cells	8,172	8,172	8,172	8,172
Country-Years	225	225	225	225
N	122,580	122,580	122,580	122,580

Table 9: presents the auto-regressive models summarized in Table 3. Standard errors are clustered on cell.

C. Effect of Prices on Conflict Near Existing Infrastructure

C.1 Relationship between Conflict and Local Gas Prices

Table 10: Past Conflict and Local Gas Prices

	Local Gas Price					
Battles (t-1, logged)	0.006 (0.019)	0.017 (0.023)				
Rebel Battles (t-1, logged)			0.015 (0.018)	0.016 (0.016)		
Eth. Militia or Rebel Battles (t-1, logged)					0.011 (0.019)	0.018 (0.019)
Controls from Mahdavi et al. (2022)		✓		✓		✓
Countries	47	41	47	41	47	41
Years	12	12	12	12	12	12
N	534	462	534	462	534	462

Table 10 presents OLS models with standard errors clustered on country. The dependent variable is the local gasoline price from Ross et al. (2017). Even columns include the covariates suggested by Mahdavi et al. (2022). The conflict variables count the number of cells experiencing a given form of conflict in a country-year. These conflict variables are lagged one year and transformed using $\log(x+1)$. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

C.2 Including Additional Time-varying Controls

Table 11: Effect of Local and Global Fuel Prices on Armed Conflict around Existing Infrastructure (with Controls)

	Battle	Rebel Battle	Rebel or Eth. Militia Battle
Log(Local Price) x Pipeline (γ_1)	0.057 (0.113)	0.112* (0.061)	0.105 (0.066)
Log(Global Price) x Pipeline (γ_2)	-0.003 (0.083)	-0.115** (0.057)	-0.109* (0.060)
Equivalence Test ($H_0 : \gamma_1 = \gamma_2$)	0.75	0.05	0.07
Controls	✓	✓	✓
Cells	1,457,414	1,457,414	1,457,414
Country-Years	536	536	536
N	17,123,381	17,123,381	17,123,381

Table 11 presents a reanalysis of Table 4 with added controls for population and nightlights. Models estimated using OLS with standard errors clustered at the grid cell level. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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D. Evidence from Other Cases

D.1 Colombia: Oil pipeline attacks and oil theft, 1986–2014

Crude oil is Colombia’s most valuable export commodity. The country’s oil infrastructure — including over 15,000 km of oil, gas, and product pipelines (Central Intelligence Agency, n.d.) — has been the victim of thousands of attacks over decades by armed groups including the left-wing guerrilla groups the ELN and the FARC, most along pipelines. Both groups “have extracted so-called ‘war taxes’ from oil companies and local contractors, using kidnaps, extortion and bombings of oil pipelines as leverage,” and are also paid by municipal governments a share of their oil revenues (Dunning and Wirpsa 2004). Indeed, competition between the two for these side payments from oil companies, contractors, and the government led the FARC in the late 1990s to “increase pipeline bombings in an attempt to wrest rents channeled to the ELN” (Dunning and Wirpsa 2004). Between when one pipeline, Caño Limón-Coveñas, was constructed in 1986 and 2014, there were 1,317 attacks causing the pipeline to be shut off for 3,701 days at a loss of USD 611 million including spilled oil and repair costs alone (Cuéllar 2016). Dube and Vargas (2013) document evidence of oil theft by several armed groups, most notably the right-wing paramilitaries, suggesting that just in the two year period between 2001 and 2003 USD 10 million of oil was stolen.

The features of the case match assumptions and implications of our formal model, as in the Nigeria case. The armed groups attack pipelines, the less valuable and more difficult to defend portions of the oil infrastructure, and not terminals or wells. The groups engage both in theft and sabotage attacks that force government to the bargaining table. And the state, as well as oil companies, respond to the groups who have demonstrated their ability to interrupt oil production, with the “war taxes.”

D.2 Turkey: Pipeline attacks and oil theft in southeastern Turkey, 2009–16

The Kurdistan Workers’ Party (PKK), founded in 1974 to fight for a secessionist state in southeastern Turkey, has relied on pipeline attacks since the early 1980s. The group’s demands of the Turkey government include “the Kurdish identity be recognized, and that Kurds be able to freely exercise their civic rights through constitutional guarantees. They also seek some form of autonomy in the Kurdish areas (east and southeast of the country) where they are concentrated” (Savran 2020: 778).

Pipeline attacks preceded several major episodes of bargaining between the Turkish government and the PKK. In 2009, Prime Minister Tayyip Erdogan announced the “Kurdish Opening,” the beginning of a peace process with the PKK. The proposed concessions included “greater cultural rights for Kurds, some form of local autonomy, and incentives to Kurdistan Workers’ Party (PKK) fighters to lay down arms” (International Peace 2009). The move followed a series of pipeline

bombings perpetrated by the PKK in May, August, and November 2008 (Weiss et al. 2012). The negotiations stalled but began again in 2013, preceded by a series of bombings in late 2012 claimed by the PKK (BBC 2012). The negotiations in 2013 led to a ceasefire, but resumed in 2015 when the talks broke down (Coskun 2015). None of these negotiations led to implementation of the concessions, interrupted by outside events in the war against ISIS or violations of ceasefires.

After several pipeline attacks in 2015, the government announced heightened pipeline security, deploying patrols on horseback and thermal cameras. A think-tank expert warned: “Even the best security plan would not be able to stop attacks. We’re talking about hundreds of kilometers of pipelines being patrolled 24/7 – that’s not possible” (Coskun and Pamuk 2015).

Turkey, and especially the southeastern region that is the homeland of the PKK, has been a hotspot for oil and fuel smuggling, oil theft, and local refining (Bozcali 2011). The government accuses the PKK of involvement in oil theft. For example, in 2016, the government arrested 27 accused members of the PKK and seized nearly 200,000 liters of crude, saying that “suspects set up a small refinery to convert crude oil to fuel” and that “[r]evenues were used to finance the activities of the PKK” (Staff 2016).

The PKK case matches overlaps in important ways with our formal framework. The armed group engages both in sabotage attacks of oil infrastructure and in oil theft, it focuses nearly all of its attacks on difficult-to-defend pipelines and not on other infrastructure like terminals, and the government has responded to its demands by offering concessions in line with its demands (though they did not follow through on implementing these concessions). The group profits from the presence of the oil industry through theft but also seeks to use its attacks to demand the government finally respond to longstanding grievances of the Kurdish ethnic group.

D.3 Egypt: Gas pipeline attacks in the northern Sinai Peninsula, 2011-12

Egypt is a major producer of both oil and natural gas. The 1,200-km Arab Gas Pipeline crosses the Sinai and connects Egypt’s gas pipeline grid with its neighbors in Lebanon, Jordan, Syria, and, at the time, Israel. In 2011 and 2012, pipelines in the Sinai were attacked more than a dozen times (Stocker 2012), leading to shutdowns and economic losses in Egypt and the countries the gas was delivered to on the order of billions of dollars. Nomadic Bedouin groups who historically populated the Sinai desert were allegedly behind, or complicit, in the attacks. The groups, who share more historical ties with groups across the border in Gaza and Israel than with Egyptians, harbor a series of grievances regarding political autonomy and repression under the Mubarak regime. A Bedouin leader wanted by the Egyptian police wrote in letter to the Egypt Independent in 2010, during a campaign of violence that preceded the pipeline attacks: “We are forced to use illicit methods to secure a livelihood for the government has left us with no alternative” (El-Dalah 2010). In talks with the government over the pipeline attacks, Bedouin leaders demanded an amnesty

for Bedouins accused in the violence, payments to tribes whose land the pipelines traverse, hiring Bedouins to protect pipelines, and other political demands that shift local decision making power from the central government to the Bedouins. Not all of these demands were met, but the Egyptian government did offer protection money payments to Bedouin groups to safeguard the pipelines (Pelham 2012).³²

The outlines of this case also link to our formal framework. It is the long, difficult-to-defend gas pipelines in the desert that are attacked, and not the terminals in the cities. Though the Bedouins do not appear to engage in oil theft, there was some contemporaneous uncertainty about exactly who undertook the attacks and the government may have worried about the risk of theft by the violent extremist groups present in the Sinai at the time. The state, as in the model, responds with protection payments to the demands of the Bedouins, who demonstrated their strength in interrupting gas production.

D.4 Mexico: Oil pipeline attacks and theft of crude oil and petroleum products, 2007

Mexico has over 50,000 km of oil and gas pipelines crisscrossing the country. At several points in recent decades, armed groups have attacked them in order to achieve political aims. Oil theft has also become increasingly common. In 2007, for example, a leftist armed group, Ejército Popular Revolucionario (EPR), launched a series of attacks using plastic explosives and potassium nitrate on natural gas pipelines that run from the Gulf of Mexico to the interior (Tobar 2007). The attacks caused economic losses on the order of hundreds of millions of dollars (McKinley and Betancourt 2007). The group described the attacks as the start of a “campaign of harassment against the interests of the oligarchy and this illegitimate government has been launched” (Comandancia military de zona del Ejército Popular Revolucionario 2007). EPR was, at the time, thought to have minimal military capacity, perhaps less than 100 fighters. The group demanded the release of two of their leaders that they said had been detained in Oaxaca by the federal government. EPR was founded in the mid-1990s with the goal of overthrowing the Mexican state, in response to rising inequality and state oppression (Comandancia general del Ejército Popular Revolucionario 1996). Armed groups — but notably not the EPR — have engaged in oil theft for several decades in Mexico, labeled “huachicoleros” or oil thieves. Recent estimates suggest that USD 1 billion of petroleum products, mostly fuels, is stolen each year (Hunn 2017). In 2018, the state-owned PEMEX which at the time controlled most of the pipeline infrastructure in the country, it discovered 15,000 illegal oil taps in its pipelines (Peschard Mariscal et al. 2021). Many armed groups are involved in oil theft in Mexico, particularly the powerful drug trafficking organizations.

Several features of the EPR case align with our formal framework, but there is some ambiguity. The group focuses attacks on pipelines, not other energy infrastructure, as our framework

32. See also Barkat (2012).

predicts. With little ability to challenge the state militarily, the group used this “weapons of the weak” strategy to force the state to the bargaining table. Though the EPR did not engage in oil and gas theft, other groups did; as a result, it is possible the government believed the EPR could have, increasing the credibility of the group’s bargaining position. The state did not at least publicly respond to these attacks, perhaps because they did not continue, demonstrating the weakness of the group. They were clearly worried, however, and paying attention.

E. Proofs

E.1 Proof of Proposition I

Lemma 1. *For every actor $i = G, A$, the following hold:*

1. $\sum_n s_n^i(\sigma^i) = S^i$ for every $\sigma^i \in \Delta(\mathcal{L}^i)$.
2. for every $x \in [0, 1]^N$ such that $\sum_n x_n = S^i$, there exists $\sigma^i \in \Delta(\mathcal{L}^i)$ such that $s_n^i(\sigma^i) = x_n$ for all $n = 1, \dots, N$.

Proof. The first result follows from the definition of s_n^i and the assumption that for all $l^i \in \mathcal{L}^i$, we must have $\sum_n l_n^i = S^i$. To prove the second result, fix $x \in [0, 1]^N$ such that $\sum_n x_n = S^i$. Define the function $f^i : \Delta(\mathcal{L}^i) \rightarrow \Delta(\mathcal{L}^i)$ as

$$f_{l^i}^i(\sigma^i) = \frac{\sigma^i(l^i) + \frac{1}{\kappa^i} \sum_n l_n^i \cdot \max\{0, x_n - s_n^i(\sigma^i)\}}{1 + \sum_n \max\{0, x_n - s_n^i(\sigma^i)\}}.$$

where $f^i(\sigma^i) = \times_{l^i \in \mathcal{L}^i} f_{l^i}^i(\sigma^i)$ and $\kappa^i = \binom{N-1}{S^i-1} > 0$ is a normalizing constant. Notice f^i is continuous. Furthermore, for all σ^i , $f_{l^i}^i(\sigma^i) \geq 0$ as $f_{l^i}^i$ is the ratio of two non-negative numbers (with a positive denominator). In addition, it is straightforward to show that the codomain of f^i is indeed $\Delta(\mathcal{L}^i)$, which is convex, compact, and nonempty. So f^i has a fixed point by Brouwer’s Theorem. At a fixed point, we must have $x_n - s_n^i(\sigma^i) = 0$ for all n . \square

Define i ’s expected value added from locating at section n given σ^{-i} as $V_n^i(\sigma^{-i})$:

$$V_n^A(\sigma^G) = \begin{cases} \theta v^A(1 - s_n^G(\sigma^G)) & \text{if } n \leq N^c \\ v^A(1 - s_n^G(\sigma^G)) & \text{if } n > N^c \end{cases}$$

and

$$V_n^G(\sigma^A) = \begin{cases} \theta v^G s_n^A(\sigma^A) & \text{if } n \leq N^c \\ v^G s_n^A(\sigma^A) & \text{if } n > N^c \end{cases}.$$

At times we may suppress notation and write V_n^i instead of $V_n^i(\sigma^{-i})$ when it is clear that V_n^i depends on σ^{-i} . Notice that $V_n^G(\sigma^A) = 0$ if and only if $s_n^A(\sigma^A) = 0$ and $V_n^A(\sigma^G) = 0$ if and only if $s_n^G(\sigma^G) = 1$. In addition, $V_n^i(\sigma^{-i}) \geq 0$ and $V_n^i(\sigma^{-i}) \leq v^i(\theta \mathbb{I}[n \leq N^c] + \mathbb{I}[n > N^c])$ for all i and n .

The next result follows from manipulating the definitions of U^i , s_n^i and V_n^i . Namely, due to the linearity of expectation and the independence of the mixed strategies, i 's expected total payoffs are the sum of expected section-specific payoffs.

Lemma 2. *Given strategy profile σ , we can write i 's expected utility from choosing locations l^i as*

$$U^A(l^A; \sigma^G) = \sum_n l_n^A \cdot V_n^A(\sigma^G) \quad \text{and} \quad U^G(l^G; \sigma^A) = - \sum_n (1 - l_n^G) V_n^G(\sigma^A)$$

Furthermore, $U^A(\sigma) = \sum_n s_n^A(\sigma^A) V_n^A(\sigma^G)$ and $U^G(\sigma) = - \sum_n (1 - s_n^G(\sigma^G)) V_n^G(\sigma^A)$.

The next result establishes two properties that must hold in every equilibrium.

Lemma 3. *If σ is an equilibrium, then for all sections n and n' the following hold:*

1. $s_n^i, s_{n'}^i \in (0, 1)$ implies $V_n^i = V_{n'}^i$.
2. $V_n^i < V_{n'}^i$ and $s_n^i > 0$ imply $s_{n'}^i = 1$.

Proof. We prove Lemma 3.1 and the proof for 3.2 follows along similar lines. Suppose not. Then there exists an equilibrium $\sigma = (\sigma^G, \sigma^A)$ and sections n^* and n' such that $s_{n^*}^i, s_{n'}^i \in (0, 1)$ and $V_{n^*}^i \neq V_{n'}^i$. Without loss of generality, assume $V_{n^*}^i < V_{n'}^i$. Define $x \in [0, 1]^N$ such that

$$x_n = \begin{cases} s_n^i & \text{if } n \notin \{n^*, n'\} \\ s_{n'}^i + \varepsilon & \text{if } n = n' \\ s_{n^*}^i - \varepsilon & \text{if } n = n^* \end{cases}$$

where $0 < \varepsilon < \min\{1 - s_{n'}^i, s_{n^*}^i\}$. Notice $x_n = s_n^i$ for all $n \notin \{n^*, n'\}$, and $x_{n^*} + x_{n'} = s_{n^*}^i + s_{n'}^i$. So $\sum_n x_n = S^i$. By Lemma 1, there exists $\tilde{\sigma}^i \in \Delta(\mathcal{L}^i)$ such that $s_n^i(\tilde{\sigma}^i) = x_n$ for all sections n .

Furthermore, i can profitably deviate to strategy $\tilde{\sigma}^i$. To see why, suppose $i = A$. By Lemma 2, we can write the net gain from deviating as as

$$\begin{aligned}
U^A(\tilde{\sigma}^A, \sigma^G) - U^A(\sigma) &= \sum_n [s_n^A(\tilde{\sigma}^A)V_n^A - s_n^A(\sigma^A)V_n^A] \\
&= x_{n^*}^A V_{n^*}^A + x_{n'}^A V_{n'}^A - s_{n^*}^A V_{n^*}^A - s_{n'}^A V_{n'}^A \\
&= (x_{n^*}^A - s_{n^*}^A)V_{n^*}^A + (x_{n'}^A - s_{n'}^A)V_{n'}^A \\
&= -\varepsilon V_{n^*}^A + \varepsilon V_{n'}^A = \varepsilon(V_{n'}^A - V_{n^*}^A) > 0
\end{aligned}$$

where the last inequality follows because $V_{n^*}^i < V_{n'}^i$. A similar argument shows that we can also construct a profitable deviation when $i = G$. \square

We are now ready to prove the proposition.

Proof of Proposition 1. In a fully mixed equilibrium, Lemma 3.1 implies $V_n^A = V_{n'}^A$ for all sections n , and n' . When $n, n' \leq N^c$, this implies $s_n^G = s_{n'}^G \equiv \gamma^c \in (0, 1)$. When $n, n' > N^c$, this implies $s_n^G = s_{n'}^G \equiv \gamma^p \in (0, 1)$. So the government is defending pieces of critical infrastructure with probability γ^c and defending pieces of the pipeline with probability γ^p . When $n \leq N^c < n'$, we must have

$$V_n^A = \theta v^A(1 - \gamma^c) = v^A(1 - \gamma^p) = V_{n'}^A. \quad (4)$$

Here, Equation (4) is A 's indifference condition between attacking critical infrastructure n and attacking pipeline section n' . From Lemma 1.1, we have a feasibility constraint for the government:

$$\sum_n s_n^G = N^c \gamma^c + N^p \gamma^p = S^G. \quad (5)$$

Solving Equations (4) and (5) gives $\gamma^c = \frac{S^G + N^p(\theta - 1)}{N^c + \theta N^p}$ and $\gamma^p = \frac{N^c + \theta(S^G - N^c)}{N^c + \theta N^p}$.

Equations (4) and (5) have counterparts that are used to derive the armed group's probability of attacking. Namely, let $\rho^c \in (0, 1)$ denote the probability that group attacks critical pieces and let $\rho^p \in (0, 1)$ denote the probability that group attacks pipeline pieces. For $n \leq N^c < n'$, the government's indifference condition is $V_n^G = \theta v^G \rho^c = v^G \rho^p = V_{n'}^G$. The group's feasibility constraint is $\sum_n s_n^A = N^c \rho^c + N^p \rho^p = S^A$. Solving these two equations gives $\rho^c = \frac{S^A}{N^c + \theta N^p}$ and $\rho^p = \frac{\theta S^A}{N^c + \theta N^p}$.

Using Lemma 2 and the previously derived mixed strategies, it is straightforward to compute equilibrium expected utilities. \square

E.2 Proof of Proposition II

E.2.1 Existence

Let s_n^i denote the probability that actor i locates at section n in a fully mixed equilibrium, as stated in Proposition I. To see that a fully mixed equilibrium exists if and only if $S^G > \frac{\theta-1}{\theta}$ and $S^A < N^p + \frac{N^c}{\theta}$, we establish these two intermediate claims:

- (a) $s_n^G \in (0, 1)$ for all n if and only if $S^G > \frac{\theta-1}{\theta}N^c$
- (b) $s_n^A \in (0, 1)$ for all n if and only if $S^A < N^p + \frac{N^c}{\theta}$

To see (a), first consider section $n \leq N^c$. So $s_n^G = \frac{S^G + (\theta-1)N^p}{N^c + \theta N^p}$. The denominator and numerator are positive so $s_n^G > 0$. For $s_n^G < 1$, we need

$$S^G + (\theta - 1)N^p < N^c + \theta N^p \iff S^G < N^c + N^p,$$

which holds by assumption $S^G < N$. Consider section $n > N^c$ where $s_n^G = \frac{N^c + \theta(S^G - N^c)}{N^c + \theta N^p}$. The numerator is positive if and only if

$$N^c + \theta(S^G - N^c) > 0 \iff S^G > \frac{\theta - 1}{\theta}N^c.$$

To see that $s_n^G < 1$, note that

$$s_n^G < 1 \iff N^c + \theta(S^G - N^c) < N^c + \theta N^p \iff \theta S^G < \theta(N^p + N^c),$$

which holds because $\theta > 1$ and $S^G < N$.

To see (b), note that $S^A < N^c + N^p$ and $\theta > 1$ imply that (i) $s_n^A > 0$ for all n and (ii) $s_n^A < 1$ for $n \leq N^c$. For $n > N^c$, rearranging the expression in Proposition I gives $s_n^A < 1 \iff S^A < N^p + \frac{N^c}{\theta}$.

Thus, the marginal distributions in Proposition I satisfy $s_n^i \in (0, 1)$ for all n and i if and only if $S^G > \frac{\theta-1}{\theta}N^c$ and $S^A < N^p + \frac{N^c}{\theta}$. By construction, $\sum_n s_n^i = S^i$ for all i . Thus, when $s_n^i \in (0, 1)$ for all n and i , Lemma 1 implies that there exist a strategy profile σ that produces these marginal distributions. Under σ , $V_n^i = V_{n'}^i$ for all n, n' and all i by the construction of the marginal distribution. As such, $U^i(l^i; \sigma^{-i}) = U^i(\sigma)$ for all i and all $l^i \in \mathcal{L}^i$. So there is no profitable deviation.

E.2.2 Uniqueness

The goal is to prove that, if $S^G > \frac{\theta-1}{\theta}N^c$ and $S^A < N^p + \frac{N^c}{\theta}$, then all equilibria are fully mixed. Note that if the armed group is playing a fully mixed strategy in equilibrium σ —i.e., $s_n^A \in (0, 1)$ for all n —then s^G will take the form stated in Proposition I to satisfy the armed group's indifference condition in Equation 4 subject to the government's budget constraint in Equation 5. Then $S^G > \frac{\theta-1}{\theta}N^c$ implies $s_n^G \in (0, 1)$ for all n , which means the government would be fully mixing. Thus, it

suffices to show that $S^G > \frac{\theta-1}{\theta}N^c$ and $S^A < \frac{N^c+\theta N^p}{\theta}$ are jointly sufficient for the armed group to be fully mixing in every equilibrium.

Lemma 4. *In every equilibrium σ , $s_n^A = 0$ implies $s_n^G = 0$.*

Proof. To see this, suppose not. Then there exist an equilibrium σ and a section n^* such that $s_{n^*}^A = 0 < s_{n^*}^G$. By Lemma 1, $V_{n^*}^G = 0$. Now consider some n such that $s_n^A > 0$. By definition, $V_n^G > 0$. By Lemma 3.2, $V_n^G > V_{n^*}^G$ and $s_{n^*}^G > 0$ imply $s_n^G = 1$. So A is only attacking sections that are defended with probability one. As such, $U^A(\sigma) = 0$. It is thus straightforward to find a profitable deviation for A . Because $\sum_{n'} s_{n'}^G = S^G$ and $S^G < N$, there exists section n^\dagger such that $s_{n^\dagger}^G < 1$, which implies $V_{n^\dagger}^A > 0$. Consider some $l^A \in \mathcal{L}^A$ such that $l_{n^\dagger}^A = 1$. Then $U^A(l^A; \sigma^G) \geq V_{n^\dagger}^A > 0 = U^A(\sigma)$. \square

Claim 1. *Assume $S^G > \frac{\theta-1}{\theta}N^c$. In every equilibrium σ , $s_n^A > 0$*

Proof. Suppose not. Then there exists an equilibrium σ and a section n^* such that $s_{n^*}^A = 0$. Thus, $s_{n^*}^G = 0$ by Lemma 4. Consider two cases.

1. $n^* \leq N^c$ implies $V_{n^*}^A = \theta v^A$. Consider some n such that $s_n^A > 0$. It must be the case that $V_n^A = \theta v^A$. If not, then $V_n^A < \theta v^A = V_{n^*}^A$ and $s_{n^*}^A > 0$ imply $s_n^A = 1$ by Lemma 3, a contradiction. So A is only attacking sections n such that $n \in \{1, \dots, N^c\} \setminus \{n^*\}$ and $s_n^G = 0$. This means G can only be defending sections that are not attacked, which contradicts Lemma 4.
2. $n^* > N^c$ implies $V_{n^*}^A = v^A$. For accounting purposes, define two sets:

$$\mathcal{A}^p = \{n \mid n > N^c, s_n^A > 0\} \quad \text{and} \quad \mathcal{A}^c = \{n' \mid n' \leq N^c, s_{n'}^A > 0\}.$$

First consider some $n \in \mathcal{A}^p$. Then $V_n^A = v^A(1 - s_n^G)$. If $s_n^G > 0$, then $V_n^A < V_{n^*}^A$. Therefore, by Lemma 3.2, $s_n^A > 0$ implies $s_{n^*}^A = 1$, a contradiction. So we have $n \in \mathcal{A}^p$ implies $s_n^G = 0$. Next consider some $n \in \mathcal{A}^c$. Then $V_n^A = \theta v^A(1 - s_n^G)$. If $s_n^G > \frac{\theta-1}{\theta}$, then $V_n^A < V_{n^*}^A$. Therefore, by Lemma 3.2 $s_n^A > 0$ implies $s_{n^*}^A = 1$, a contradiction. So we have $n \in \mathcal{A}^c$ implies $s_n^G \leq \frac{\theta-1}{\theta}$. Some accounting gives us

$$\begin{aligned} \sum_n s_n^G &= \sum_{n \in \mathcal{A}^c} s_n^G + \sum_{n \in \mathcal{A}^p} s_n^G + \sum_{n \notin \mathcal{A}^p \cup \mathcal{A}^c} s_n^G \\ &= \sum_{n \in \mathcal{A}^c} s_n^G \leq (\#\mathcal{A}^c) \frac{\theta-1}{\theta} \leq N^c \frac{\theta-1}{\theta} < S^G. \end{aligned}$$

So $\sum_n s_n^G < S^G$, which contradicts Lemma 1. \square

Claim 2. *Assume $S^G > \frac{\theta-1}{\theta}N^c$. In every equilibrium σ , $n \leq N^c$ and $s_n^A = 1$ imply $s_n^G = 1$.*

Proof. Suppose not. Then there exists equilibrium σ and $n^* \leq N^c$ such that $s_{n^*}^A = 1$ and $s_{n^*}^G < 1$. Then $V_{n^*}^G = \theta v^G$. Define the two sets:

$$\mathcal{D} = \{n \mid s_n^G > 0\} \quad \text{and} \quad \mathcal{A}_1^c = \{n \mid n \leq N^c, s_n^A = 1\}.$$

First, $\mathcal{D} \neq \emptyset$. Second, $\mathcal{D} \subseteq \mathcal{A}_1^c$. To see this, take some $n \in \mathcal{D}$. If $V_n^G < \theta v^G = V_{n^*}^G$, Lemma 3.2 implies $s_{n^*}^G = 1$, a contradiction. So $n \in \mathcal{D}$ implies $V_n^G = \theta v^G$. Thus, $\mathcal{D} \subseteq \mathcal{A}_1^c$, and as a consequence $\mathcal{D} \subseteq \{1, \dots, N^c\}$. Third, $\mathcal{A}_1^c = \{1, \dots, N^c\}$. It is clear that $\mathcal{A}_1^c \subseteq \{1, \dots, N^c\}$ by construction. So take some $n \leq N^c$ and suppose $n \notin \mathcal{A}_1^c$ to draw a contradiction. Then $n \notin \mathcal{D}$, which means $V_n^A = \theta v^A$. Recall $n' \in \mathcal{D}$ implies $s_{n'}^A > 0$ by Lemma 4 and $V_{n'}^A = \theta v^A(1 - s_{n'}^G) < \theta v^A = V_n^A$. So Lemma 3.2 implies $s_n^A = 1$. Thus, $\mathcal{A}_1^c = \{1, \dots, N^c\}$. Because $S^A < N^c + N^p$, there exists $n^\dagger > N^c$ such that $s_{n^\dagger}^A < 1$. By Claim 1, $s_{n^\dagger}^A > 0$. Furthermore, because $\mathcal{D} \subseteq \mathcal{A}_1^c$, $V_{n^\dagger}^A = v^A$. To rule out a profitable deviation (i.e., a contardition with Lemma 3.2), we require

$$V_{n^\dagger}^A = v^A \leq \theta v^A(1 - s_n^G) = V_n^A$$

for all $n \in \mathcal{D}$. This implies $s_n^G \leq \frac{\theta-1}{\theta}$ for all $n \in \mathcal{D}$. But $\mathcal{D} \subseteq \{1, \dots, N^c\}$, so $S^G = \sum_{n \in \mathcal{D}} s_n^G \leq \frac{\theta-1}{\theta} N^c$, a contradiction. \square

Claim 3. Assume $S^G > \frac{\theta-1}{\theta} N^c$. In every equilibrium σ , $n \leq N^c$ implies $s_n^G > 0$

Proof. Suppose not. So there exists an equilibrium σ and section $n^* \leq N^c$ such that $s_{n^*}^G = 0$. This implies $V_{n^*}^A = \theta v^A$. By Claim 2, $s_{n^*}^A < 1$. We claim that A is only attacking undefended pieces of critical infrastructure, i.e., $s_n^A > 0$ implies $V_n^A = \theta v^A$. To see this, suppose not. Then $s_n^A > 0$ and $V_n^A < \theta v^A = V_{n^*}^A$ for some n . But then Lemma 3.2 implies $s_{n^*}^A = 1$, a contradiction. Because A is only attacking undefended pieces of critical infrastructure, this means G is defending sections that are not attacked, contradicting Lemma 4. \square

Claim 4. Assume $S^G > \frac{\theta-1}{\theta} N^c$ and $S^A < \frac{N^c + \theta N^p}{\theta}$. In every equilibrium σ , there exists $n > N^c$ such that $s_n^A < 1$.

Proof. Suppose not. Then there exists equilibrium σ such that $s_n^A = 1$ for all $n > N^c$. Obviously, $S^A \geq N^p$, but we must also have $S^A > N^p$. If not, then $N^p = S^A$, which means sections $n \leq N^c$ have $s_n^A = 0$, contradicting Claim 1.

We claim that $n > N^c$ implies $s_n^G = 1$. To see this suppose not. Then there exists $n^* > N^c$ such that $s_{n^*}^G < 1$. Take some $n' \leq N^c$. By Claim 3, we have $s_{n'}^G > 0$. By Lemma 3.2, we need $V_{n'}^G \geq V_{n^*}^G$

or else $s_{n'}^G > 0$ would imply $s_{n'}^G = 1$. That is, we must have

$$V_{n'}^G = v^G \leq V_{n'}^G = \theta v^G s_{n'}^A,$$

for all $n' \leq N^c$, which holds if and only if $s_{n'}^A \geq \frac{1}{\theta}$. Accounting reveals that

$$S^A = \sum_{n''} s_{n''}^A = \sum_{n'' \leq N^c} s_{n''}^A + \sum_{n'' > N^c} s_{n''}^A \geq \frac{N^c}{\theta} + N^p,$$

a contradiction.

Now because $S^G < N^p + N^c$ and G is surely defending $n > N^c$, there exists an $n^\dagger \leq N^c$ such that $s_{n^\dagger}^G < 1$. Recall for $n > N^c$ we have $s_n^A = 1$ and $V_{n^\dagger}^A > 0 = V_n^A$. Thus Lemma 3.2 implies $s_{n^\dagger}^A = 1$, but then Claim 2 implies $s_{n^\dagger}^G = 1$, a contradiction. \square

Claim 5. Assume $S^G > \frac{\theta-1}{\theta}N^c$ and $S^A < \frac{N^c+\theta N^p}{\theta}$. In every equilibrium σ , there exists $n > N^c$ such that $s_n^A < 1$ and $s_n^G < 1$.

Proof. Suppose not. Then, for all $n > N^c$ such that $s_n^A < 1$, we have $s_n^G = 1$. To draw a contradiction, we first establish that $n > N^c$ and $s_n^A = 1$ imply $s_n^G = 1$. To see this, note that $n > N^c$ and $s_n^A = 1$ imply $V_n^G = v^G$. By Claim 4, there exists $n^* > N^c$ such that $s_{n^*}^A < 1$. By the supposition, $s_{n^*}^G = 1$ and $V_{n^*}^G = v^G s_{n^*}^A < v^G = V_n^G$. Thus, Lemma 3.2 implies $s_n^G = 1$. So we have $n > N^c$ implies $s_n^G = 1$, i.e., $V_n^A = 0$.

Because $S^G = \sum_n s_n^G < N^c + N^p$, there exists $n^\dagger \leq N^c$ such that $s_{n^\dagger}^G < 1$. If $s_{n^\dagger}^A = 1$, then Claim 2 implies $s_{n^\dagger}^G = 1$, a contradiction. So $s_{n^\dagger}^A < 1$. Because $s_{n^\dagger}^G < 1$, $V_{n^\dagger}^A > 0 = V_n^A$ for every $n > N^c$. By Claim 1, $s_n^A > 0$ for all $n > N^c$. Thus, Lemma 3.2 implies $s_{n^\dagger}^A = 1$, a contradiction. \square

Claim 6. Assume $S^G > \frac{\theta-1}{\theta}N^c$ and $S^A < \frac{N^c+\theta N^p}{\theta}$. In every equilibrium σ , $s_n^G < 1$.

Proof. Suppose the contrary. Suppose there exists n^* such that $s_{n^*}^G = 1$, which means $V_{n^*}^A = 0$. By Claim 5, there exists $n^\dagger > N^c$ such that $s_{n^\dagger}^A < 1$ and $s_{n^\dagger}^G < 1$, which means $V_{n^\dagger}^A > 0$ and $n^\dagger \neq n^*$. By Claim 1, we have $s_{n^*}^A > 0$. So $V_{n^*}^A < V_{n^\dagger}^A$ and Lemma 3.2 imply $s_{n^\dagger}^A = 1$, a contradiction. \square

Claim 7. Assume $S^G > \frac{\theta-1}{\theta}N^c$ and $S^A < \frac{N^c+\theta N^p}{\theta}$. In every equilibrium σ , $n \leq N^c$ implies $s_n^A \in (0, 1)$.

Proof. Consider some $n \leq N^c$. By Claim 1, we have $s_n^A > 0$. If $s_n^A = 1$, then Claim 2 implies $s_n^G = 1$, but this contradicts Claim 6. \square

Claim 8. Assume $S^G > \frac{\theta-1}{\theta}N^c$ and $S^A < \frac{N^c+\theta N^p}{\theta}$. In every equilibrium σ , $n > N^c$ implies $s_n^A \in (0, 1)$.

Proof. By Claim 1, we just need to show $s_n^A < 1$ for all $n > N^c$. Suppose not. That is, suppose there exists $n^* > N^c$ such that $s_{n^*}^A = 1$. So $V_{n^*}^G = v^G$. By Claim 6, $s_{n^*}^G < 1$. Thus, $s_{n^*}^G > 0$ implies $V_{n^*}^G \geq v^G$, or else there is a contradiction with Lemma 3.2. So G is defending sections n such that (i) $n \leq N^c$ and $s_n^A \geq \frac{1}{\theta}$ or (ii) $n > N^c$ and $s_n^A = 1$.

By Claim 5, there exists $n^\dagger > N^c$ such that $s_{n^\dagger}^A < 1$ and $s_{n^\dagger}^G < 1$. Of course, $n^* \neq n^\dagger$. In addition, (ii) implies $s_{n^\dagger}^G = 0$, which means $V_{n^\dagger}^A = v^A$.

Consider some $n > N^c$. By Claim 1, $s_n^A > 0$. If $V_n^A < v^A = V_{n^\dagger}^A$, then Lemma 3.2 implies $s_{n^\dagger}^A = 1$, a contradiction. So $V_n^A = v^A$ implying $s_n^G = 0$. So we have $n > N^c$ implies $s_n^G = 0$. Second, consider some $n \leq N^c$, and again we must have $s_n^A > 0$ by Claim 1. So $V_n^A = \theta v^A(1 - s_n^G)$. As before, Lemma 3.2 implies $V_n^A \leq V_{n^\dagger}^A$, which means $s_n^G \leq \frac{\theta-1}{\theta}$. So we have $n \leq N^c$ implies $s_n^G \leq \frac{\theta-1}{\theta}$. Summing up gives us

$$\sum_n s_n^G = \sum_{n \leq N^c} s_n^G + \sum_{n > N^c} s_n^G \leq N^c \frac{\theta-1}{\theta} < S^G.$$

So $\sum_n s_n^G < S^G$, which contradicts Lemma 1. □

E.3 Proof of Proposition IV

In every equilibrium, the armed group chooses to attack in the final phase if $x < W^A - c$, and they do not attack if $x > W^A - c$. Thus, when A expects the government to use strategy $\chi = (\chi_0, \chi_1)$, we can write A 's expected payoffs from choosing $a_1 \in \{0, 1\}$ in phase 1 as $EU^A(a_1|\chi, c) = a_1(W^A - c) + \max\{\chi_{a_1}, W^A - c\}$. Define the function $\Delta(c; \chi)$ as

$$\begin{aligned} \Delta(c; \chi) &= EU^A(1|\chi, c) - EU^A(0|\chi, c) \\ &= W^A - c + \max\{\chi_1, W^A - c\} - \max\{\chi_0, W^A - c\}. \end{aligned}$$

So $\Delta(c; \chi)$ is A 's payoff difference between attacking and not in the first phase with cost c and expected offers $\chi = (\chi_0, \chi_1)$. When $\Delta(c; \chi) > 0$, A strictly prefers to attack in the first phase with cost c , and when $\Delta(c; \chi) < 0$, A strictly prefers to not attack. It satisfies the single-crossing property.

Lemma 5. Fix the government offers $\chi = (\chi_0, \chi_1)$ such that $\chi_0 \geq 0$ and $\chi_1 \geq 0$. The function $\Delta(c; \chi)$ satisfies the single-crossing property with respect to c : if there exists c^* such that $\Delta(c^*; \chi) = 0$, then $c < c^*$ implies $\Delta(c; \chi) > 0$ and $c > c^*$ implies $\Delta(c; \chi) < 0$.

Proof. Define the function $f(c; \chi) = \max\{\chi_1, W^A - c\} - \max\{\chi_0, W^A - c\}$. We prove the lemma by considering two cases: $\chi_1 > \chi_0$ and $\chi_1 \leq \chi_0$.

Case 1: $\chi_1 > \chi_0$. Then the function $f(c; \chi)$ is weakly increasing in c . Furthermore, for all c , $f(c; \chi) \in \{0, \chi_1 - W^A + c, \chi_1 - \chi_0\}$ and $f(c; \chi) \geq 0$. To see that $f(c; \chi)$ is bounded above by $\chi_1 - \chi_0$, suppose not. So $f(c; \chi) > \chi_1 - \chi_0 > 0$. Then $f(c; \chi) = \chi_1 - W^A + c$. Because $f(c; \chi) = \chi_1 - W^A + c > \chi_1 - \chi_0$, $\chi_0 > W^A - c$. This means $\max\{\chi_0, W^A - c\} = \chi_0$ and $\max\{\chi_1, W^A - c\} = \chi_1$ as $\chi_1 > \chi_0$ in this case. So $f(c; \chi) = \chi_1 - \chi_0$, a contradiction. Thus, $f(c; \chi) \leq \chi_1 - \chi_0$.

To prove the result for this case, we need to establish two intermediary claims:

1. $\Delta(c^*; \chi) = 0$ implies $\chi_0 > W^A - c^*$.
2. $\Delta(c^*; \chi) = 0$ implies $f(c^*; \chi) = \chi_1 - \chi_0$.

To prove the first claim, suppose not. Then $\Delta(c^*; \chi) = 0$ and $\chi_0 \leq W^A - c^*$. Therefore, we can write

$$\begin{aligned} \Delta(c^*; \chi) &= W^A - c^* + \max\{W^A - c^*, \chi_1\} - \max\{W^A - c^*, \chi_0\} \\ &= W^A - c^* + \max\{W^A - c^*, \chi_1\} - (W^A - c^*) \\ &= \max\{W^A - c^*, \chi_1\} > 0, \end{aligned}$$

where the final strict inequality follows because $\chi_1 > \chi_0 \geq 0$. But $\Delta(c^*; \chi) > 0$ is a contradiction. To prove the second claim, note that $\Delta(c^*; \chi) = 0$ implies $\chi_0 > W^A - c^*$. So $\chi_1 > \chi_0 \geq W^A - c^*$, and $f(c; \chi) = \chi_1 - \chi_0$.

To see that Δ satisfies the single-crossing property, suppose $\Delta(c^*; \chi) = 0$. Then for any c , we can write:

$$\begin{aligned} \Delta(c; \chi) &= \Delta(c; \chi) + \Delta(c^*; \chi) = c^* - c + f(c; \chi) - f(c^*; \chi) \\ &= c^* - c + f(c; \chi) - \chi_1 + \chi_0. \end{aligned} \tag{6}$$

Above, the last equality follows from preliminary result 2 which says that $f(c^*; \chi) = \chi_1 - \chi_0$.

Now, consider some $c < c^*$. We need to show $\Delta(c; \chi) > 0$. Because $\chi_1 > \chi_0$, $W^A - \chi_1 < W^A - \chi_0$. So there are three possibilities:

- (a) Suppose $c \leq W^A - \chi_1$. Then $W^A - c \geq \chi_1 > \chi_0$. As such $f(c; \chi) = 0$. So we can write Equation 6 as

$$c^* - c - \chi_1 + \chi_0 > c^* - c - \chi_1 + W^A - c^* = W^A - c - \chi_1 \geq 0.$$

Above, the strict inequality follows from preliminary result 1 which says $\chi_0 > W^A - c^*$. The weak inequality follows from $c \leq W^A - \chi_1$.

(b) Suppose $W^A - \chi_1 < c < W^A - \chi_0$. As such $f(c; \chi) = \chi_1 - W^A + c$. So we can write Equation 6 as

$$c^* - c + \chi_1 - W^A + c - \chi_1 + \chi_0 = c^* - W^A + \chi_0 > 0,$$

where the strict inequality follows from preliminary result 1 which says $\chi_0 > W^A - c^*$.

(c) Suppose $c \geq W^A - \chi_0$. So $f(c; \chi) = \chi_1 - \chi_0$, and we can write Equation 6 as

$$c^* - c + (\chi_1 - \chi_0) - \chi_1 + \chi_0 = c^* - c > 0,$$

where $c^* > c$ by assumption.

Second, consider some $c > c^*$. We need to show $\Delta(c; \chi) < 0$. Note that $f(c; \chi) = \chi_1 - \chi_0$ because $f(c^*; \chi) = \chi_1 - \chi_0$, f is weakly increasing in c and f is bounded above by $\chi_1 - \chi_0$. Thus, Equation 6 reduces to $c^* - c < 0$, as required.

Case 2: $\chi_0 \geq \chi_1$. So $f(c; \chi)$ is weakly decreasing in c . Thus for $c < c^*$ we have

$$0 = \Delta(c^*; \chi) = W^A - c^* + f(c^*; \chi) < W^A - c + f(c^*; \chi) \leq W^A - c + f(c; \chi) = \Delta(c; \chi),$$

where the last inequality follows because $c < c^*$ and f is weakly decreasing in c . So $c < c^*$ implies $\Delta(c) > 0$. For $c > c^*$ we have

$$0 = \Delta(c^*; \chi) = W^A - c^* + f(c^*; \chi) > W^A - c + f(c^*; \chi) \geq W^A - c + f(c; \chi) = \Delta(c; \chi),$$

where the last inequality follows because $c > c^*$ and f is weakly decreasing in c . So $c > c^*$ implies $\Delta(c; \chi) < 0$. \square

As a consequence of Lemma 5, we know that if G uses a pure strategy $\chi = (\chi_0, \chi_1)$, then A 's best response is essentially (outside the case that A is of type c such that $\Delta(c; \chi) = 0$, which occurs with probability zero) a pure strategy in phase 1. This pure strategy takes the form of a cutpoint where A attacks if c is below the cutpoint and A does not attack if c is above the cutpoint. This cutpoint c^* will be implicitly defined by $\Delta(c^*; \chi) = 0$. The next result says that, under assumption $C > 2W^A$, this cutpoint falls in the interval $(0, C)$.

Lemma 6. *There does not exist an equilibrium in which the armed group uses a cutpoint strategy $c^* \leq 0$ in phase 1. If $C > 2W^A$, then there does not exist an equilibrium in which the armed group uses a cutpoint strategy $c^* \geq C$ in phase 1.*

Proof. If A with cost c does not attack in first phase, then its payoff is $EU^A(0|\chi, c) = \max\{\chi_0, W^A - c\}$. We know that A surely accepts offer χ_0 if $\chi_0 > W^A - c$. Furthermore, the government can ensure acceptance with probability 1 by offering $x = W^A$ as $\Pr(c > 0) = 1$ (because c is uniformly distributed over the interval $[0, C]$). So sequential rationality requires $\chi_0 \leq W^A$, which then implies $EU^A(0|\chi, c) \leq W^A$. If A with cost c does attack, then its payoff is

$$EU^A(1|\chi, c) = W^A - c + \max\{\chi_1, W^A - c\} \geq 2[W^A - c].$$

Thus, $c \in [0, \frac{W^A}{2})$ implies $EU^A(1|\chi, c) > EU^A(0|\chi, c)$. In addition, by the same argument as above, $\chi_1 \leq W^A$, so $EU^A(1|\chi, c) \leq W^A - c + W^A$. In addition, $\chi_0 \geq 0$, implying $EU^A(0|\chi, c) \geq 0$. Thus, $c \in (2W^A, C]$ implies $EU^A(0|\chi, c) > EU^A(1|\chi, c)$. \square

Lemma 7. *There does not exist an equilibrium in which the armed group uses cutpoint strategy $c^* \in (0, W^A)$ in phase 1.*

Proof. To draw a contradiction, suppose not. By Lemma 5, c^* solves $\Delta(c^*; \chi) = 0$, where χ is the strategy of the government. This means

$$\Delta(c^*; \chi) = 0 \iff \max\{\chi_0, W^A - c^*\} = W^A - c^* + \max\{\chi_1, W^A - c^*\}$$

Because $c^* < W^A$ by assumption, $\max\{\chi_1, W^A - c^*\} > 0$. Thus, $\chi_0 > W^A - c^*$, or else the equation above would reduce to $W^A - c^* = W^A - c^* + \max\{\chi_1, W^A - c^*\}$, a contradiction as $W^A - c^* > 0$ by assumption. Notice that A 's cutpoint strategy implies that, after observing no attack in phase 1 ($a_1 = 0$), the government's posterior can only put positive probability on types $[c^*, C]$, and $\Pr(c = c^*) = 0$ as c is distributed according to a continuous distribution with no mass points. Thus, after observing $a_1 = 0$, G believes it can guarantee acceptance by offering $x = W^A - c^*$, so sequential rationality implies that $\chi_0 \leq W^A - c^*$, a contradiction. \square

Lemma 8. *In equilibrium, if the armed group uses cutpoint strategy $c^* \in [W^A, C)$ in phase 1, then the following hold:*

$$\begin{aligned} \chi_0 &= 0, \quad \chi_1 = \min \left\{ -\frac{W^G}{3}, W^A \right\}, \quad c^* = W^A + \chi_1, \text{ and} \\ \mu(c|a_1) &= \begin{cases} \frac{1}{C-c^*} & \text{if } a_1 = 0 \text{ and } c \in (c^*, C] \\ \frac{1}{c^*} & \text{if } a_1 = 1 \text{ and } c \in [0, c^*) \\ 0 & \text{if } a_1 = 0, c \notin [c^*, C] \text{ or } a_1 = 1, c \notin [0, c^*] \end{cases}. \end{aligned}$$

Proof. First, μ follows from Bayes rule, the uniform distribution, and A 's cutpoint strategy in which they attack in phase 1 if $c < c^*$ and do not attack when $c > c^*$. Second, after observing no attack in phase 1 ($a_1 = 0$), G knows A 's cost satisfies $c \in [W^A, C]$. Furthermore, A with cost $c > W^A$ accepts any offer $x \geq 0$. Because $\Pr(c = W^A) = 0$, offer $x = 0$ will be accepted by A with probability 1. Thus, in an equilibrium where A uses cutpoint strategy $c^* \in [W^A, C)$ in phase 1, the government offers $\chi_0 = 0$ after seeing no attack. Third, by Lemma 5, A 's cutpoint strategy c^* satisfies $\Delta(c^*; \chi) = 0$:

$$\begin{aligned} \Delta(c^*; \chi) = 0 &\iff W^A - c^* + \max\{\chi_1, W^A - c^*\} - \max\{\chi_0, W^A - c^*\} = 0 \\ &\iff W^A - c^* + \chi_1 - \chi_0 = 0 \iff W^A - c^* + \chi_1 = 0. \end{aligned}$$

Above, the second biconditional follows because $\chi_{a_1} \geq 0$ and because $c^* \geq W^A$ by assumption of the lemma. The third follows because $\chi_0 = 0$. Thus, $c^* = W^A + \chi_1$. Finally, after a phase-1 attack ($a_1 = 1$), G knows $c \in [0, c^*]$. G 's optimal offer will be $x^* \in [0, W^A]$, where offer $x = W^A$ will be accepted with probability 1 and offer $x = 0$ will be accepted with probability $\int_{W^A}^{c^*} \mu(c|1)dc$. We can write G 's expected utility from offer x as

$$\begin{aligned} U_G(x|c^*, a_1 = 1) &= \overbrace{-\int_{W^A-x}^{c^*} x\mu(c|1)dc}^{x \text{ accepted}} + \overbrace{\int_0^{W^A-x} W^G\mu(c|1)dc}^{x \text{ rejected}} \\ &= \frac{1}{C} \left[(W^A - x)(W^G + x) - c^*x \right]. \end{aligned}$$

Notice $U_G(x|c^*, a_1 = 1)$ is a strictly concave function of x , with $D_x^2 U_G(x|c^*, a_1 = 1) = -\frac{2}{C}$. So the first-order condition is necessary and sufficient to characterize G 's optimal offer when it is in $(0, W^A)$:

$$D_x U_G(\chi_1|c^*, a_1 = 1) = 0 \iff (W^A - \chi_1)(W^G + \chi_1) - c^*\chi_1 = 0 \iff \chi_1 = -\frac{W^G}{3}.$$

Notice that $-\frac{W^G}{3} > 0$ because $W^G < 0$. In addition, A accepts any offer $x > W^A - c$, so G can guarantee $x = W^A$ is accepted with probability 1 as $\Pr(c > 0) = 1$. So $\chi_1 \leq W^A$ in equilibrium. This gives us $\chi_1 = \min\left\{-\frac{W^G}{3}, W^A\right\}$. \square

To complete the proof, note that, in the final phase after offer x , A accepts if $x > W^A - c$ and rejects if $x < W^A - c$. Lemma 5 shows that the armed group employs a cutpoint strategy where they attack in phase if and only if c is below the cutpoint. Furthermore, Lemmas 6 and 7 demonstrate that any cutpoint falls in the interval $[W^A, C)$. Lemma 8 then characterizes all equilibria with such a cutpoint.

F. Data Construction

F.1 ACLED Events

ACLED ID	Country	Actor 1	Actor 2	Event description	Years since pipeline construction
LBY3662	Libya	Unidentified Armed Group	Civilians	A Filipino oil worker was killed and five others wounded in a rocket attack in Zawiya. Neither the Libyan National Army nor Libya Dawn militias has admitted to launching the missiles.	5
NIG9190	Nigeria	NDA: Niger Delta Avengers	–	Members of a group known as NDA destroy a Chevron oil pipeline in Escravos. The group, who claimed responsibility for the blast, said they are fighting for a greater share of oil profits, an end to pollution and independence for the southern region, had told oil firms to leave the Delta before the end of the month.	1
SUD612	Sudan	SSDF: South Sudan Defence Forces	Military Forces of Sudan	SSDF rebels clashed with government forces in a battle for control of southern oilfields (however, prior to this weeks incident, the SSDF had been fighting alongside government forces against SPLA opposition rebels)	0
EGY1188	Egypt	Unidentified Armed Group	–	A gas pipeline is blown up for the fourth time since February.	3
EGY1355	Egypt	Police Forces of Egypt	–	One police officer was killed and another injured in Egypts Sinai during clashes with members of an Islamist group suspected of attacks on a pipeline.	3

Table A.1: Illustrative events from ACLED conflict data within 5-km of pipelines.

E.2 Gridded Panel Data

Figure A.1: Oil and Gas Infrastructure in Africa

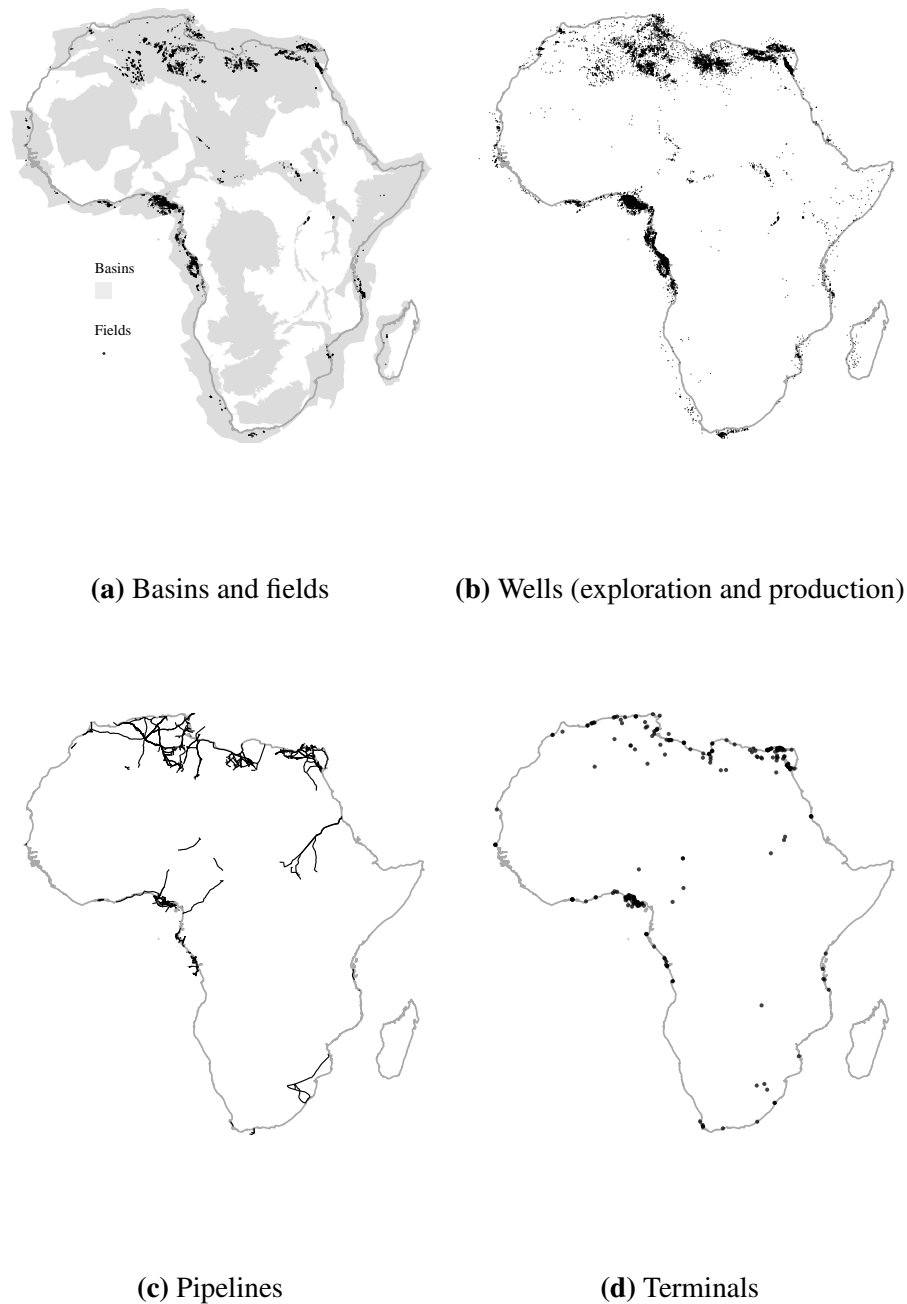


Figure A.1 displays the geography of (a) oil basins and oil and gas fields; (b) oil and gas wells, both used for exploration and production; (c) commissioned oil and gas pipelines; and (d) oil and gas terminals, such as export terminals.

Figure A.2: Example Area

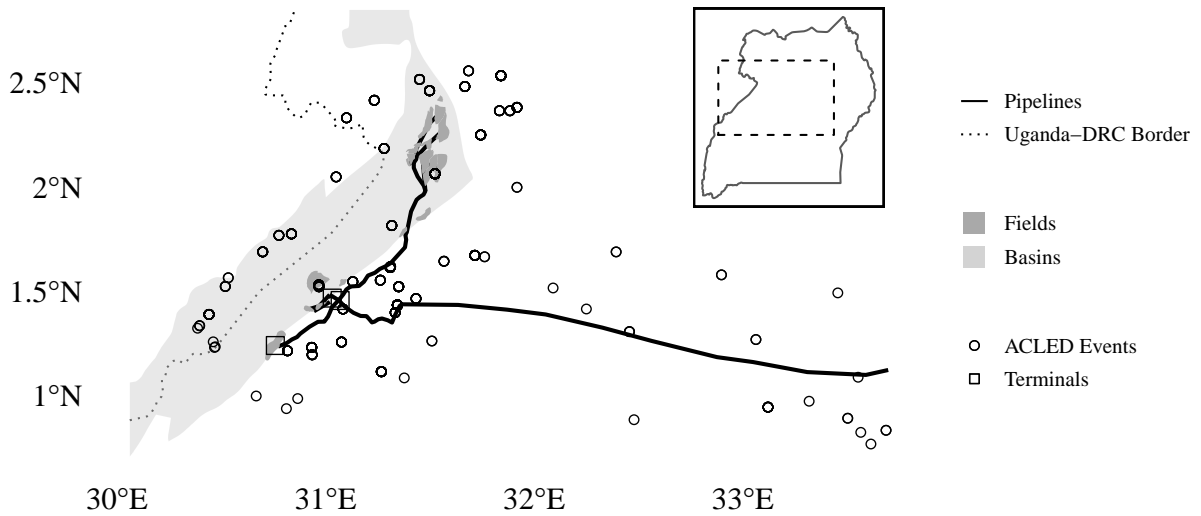


Figure A.2 is a map of an area in Uganda which will be used as an example of how we construct our cell-year panel, by associating geographic features from oil infrastructure and conflict to grid cells by year. The oil infrastructure used to construct the independent variables includes oil fields in dark gray, oil terminals in black squares, and pipelines in black. We also show the basin where oil is formed in light gray. Conflict events from ACLED are displayed in outlined circles.

Figure A.3: Construction of Cell-Year Panel

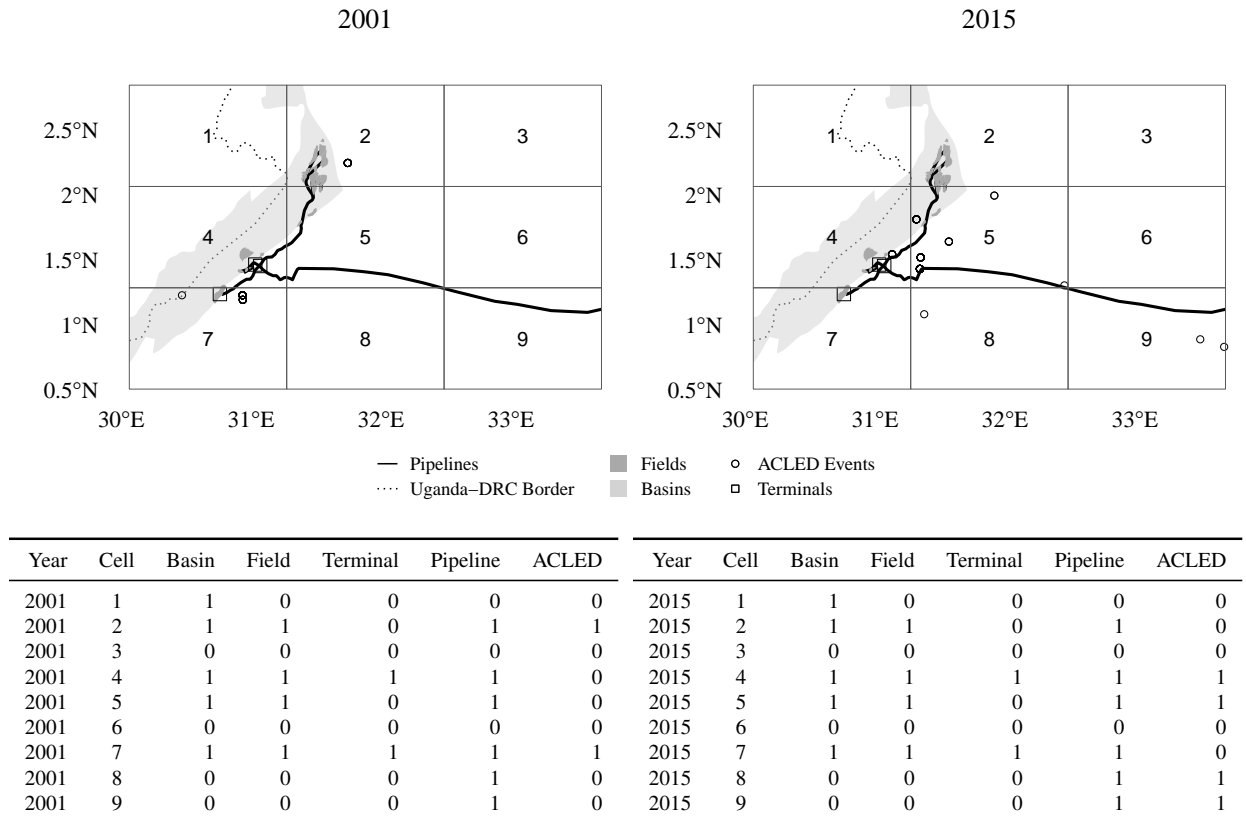


Figure A.3 illustrates the construction of the cell-year panel used in the main analyses in the paper. In the upper left, the example region displayed in Figure A.2 is divided into nine rectangles. Each rectangle is labelled with a numerical cell value and each cell can be attributed information that is contained within, e.g. whether a cell contains a (portion of) pipeline, terminal, and/or an ACLED conflict event. The time dimension of the panel is created by merging the oil infrastructure that exists in a given year to the grid as well as the conflict events that took place. In the upper left is the infrastructure that existed and the conflict events that took place in 2001. In the upper right is the same grid, but with the oil infrastructure and conflict events that took place in 2015. Below each image is the data that results, in terms of the presence of oil infrastructure (Basin, Field, Terminal, Pipeline) and conflict events (ACLED) in each cell-year.

G. Effect of New Infrastructure

G.1 Alternative clustering

Table A.2: Effect of New Infrastructure on Armed Conflict with Alternative Clustered Standard Errors

	ACLED Event	Battle	Rebel Battle	Rebel or Eth. Militia Battle
Pipeline ($\hat{\beta}_1$)	0.319	0.160	0.031	0.076
S.E. clustered by ...				
5-km grid cells	(0.059)	(0.036)	(0.014)	(0.024)
10-km	(0.066)	(0.036)	(0.014)	(0.024)
20-km	(0.070)	(0.039)	(0.016)	(0.025)
Field, Well or Terminal ($\hat{\beta}_2$)	0.032	0.026	-0.018	-0.026
S.E. clustered by ...				
5-km grid cells	(0.052)	(0.037)	(0.011)	(0.015)
10-km	(0.056)	(0.037)	(0.011)	(0.015)
20-km	(0.056)	(0.037)	(0.011)	(0.015)
Equivalence Test ($H_0 : \beta_1 = \beta_2$) with S.E. clustered by ...				
5-km grid cells	p = 0.00	p = 0.01	p = 0.01	p = 0.00
10-km	0.00	0.01	0.01	0.00
20-km	0.00	0.01	0.01	0.00
5-km Cells	1,474,363	1,474,363	1,474,363	1,474,363
10-km Cells	370,003	370,003	370,003	370,003
20-km Cells	93,171	93,171	93,171	93,171
Country-Years	869	869	869	869
N	26,538,534	26,538,534	26,538,534	26,538,534

Table A.2 presents a reanalysis of Table 2 using two alternative levels of clustering, 10x10-km clusters (containing four 5x5-km grid units of analysis), and 20x20-km grid clusters (containing 16 5x5-km grid units). Models estimated using OLS.

G.2 Alternative units of analysis

Table A.3: Effect of New Oil/Gas Infrastructure on Armed Conflict (10x10-km Grid Cells)

	ACLED Event	Battle	Rebel Battle	Rebel or Eth. Militia Battle
Pipeline	0.796*** (0.150)	0.414*** (0.094)	0.049 (0.039)	0.222*** (0.061)
Field, Well or Terminal	0.358** (0.171)	0.173 (0.117)	-0.025 (0.027)	-0.045 (0.058)
Equivalence Test	0.06	0.12	0.13	0.00
10-km Cells	370,003	370,003	370,003	370,003
Country-Years	869	869	869	869
N	6,660,054	6,660,054	6,660,054	6,660,054

Table A.3 presents a reanalysis of Table 2 with the units of analysis as 10x10-km grid cells rather than 5x5-km grid cells. Models estimated using OLS; standard errors clustered on 10x10-km grid cell. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

G.3 Placebo Tests

Table A.4: Placebo Test for New Infrastructure

	ACLED Event	Battle	Rebel Battle	Rebel or Eth. Militia Battle
Placebo Pipeline	-0.032 (0.053)	-0.007 (0.051)	-0.007 (0.025)	-0.026 (0.027)
Placebo Field, Well or Terminal	-0.015 (0.025)	-0.013 (0.013)	-0.010 (0.013)	-0.011 (0.013)
Equivalence Test	0.77	0.91	0.89	0.62
Cells	1,462,352	1,462,352	1,462,352	1,462,352
Country-Years	869	869	869	869
N	26,268,180	26,268,180	26,268,180	26,268,180

Table A.4 presents the results of a placebo (falsification) test in which we drop all post-treatment data and recode treatment as the five years prior to infrastructure construction. We cannot reject the null hypothesis of no effect for these placebo treatments.

G.4 Moderation analysis

Table A.5: Effect of New Infrastructure Moderated by the Presence of Historically Marginalized Groups

	ACLED Event	Battle	Rebel Battle	Rebel or Eth. Militia Battle
Pipeline	0.254*** (0.052)	0.159*** (0.040)	0.031* (0.016)	0.080*** (0.026)
Field, Well or Terminal	0.004 (0.038)	0.026 (0.037)	-0.015 (0.011)	-0.015 (0.013)
Pipeline × Historically Marginalized Group	0.031 (0.276)	0.204 (0.160)	0.079 (0.070)	0.101 (0.118)
Field, Well or Terminal × Historically Marginalized Group	0.312 (0.416)	-0.016 (0.171)	-0.034 (0.038)	-0.129 (0.092)
Cells	1,474,363	1,474,363	1,474,363	1,474,363
Country-Years	869	869	869	869
N	26,538,534	26,538,534	26,538,534	26,538,534

Table A.5 shows the effect of new infrastructure moderated by whether it is sited in an area where a historically marginalized group resides. Groups' statuses are coded based on whether they were discriminated against or self-excluded in the 10 years prior to our study period (1987–1996) based on the GeoEPR dataset. Models are estimated using OLS with cell and country-by-year fixed effects, with standard errors clustered on cell. We report the number of cells and country-years in the analysis as well as the total sample size. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

G.5 Diagnostics for Two-way Fixed Effects (TWFE) Estimates

A burgeoning literature in econometrics identifies potential issues with the use of TWFE estimators for staggered designs, in which the timing of treatment varies across treated units. This work provides helpful diagnostics and alternative approaches that we employ below to demonstrate the robustness of our finding that new pipeline construction increases the likelihood of armed conflict (see Table 2). Given the size of our panel, we rewrote large portions of the `TwoWayFEWeights` and `bacondecomp` packages (using `data.table` syntax) to handle our data.

G.5.1 De Chaisemartin and d’Haultfoeuille (2020)

De Chaisemartin and d’Haultfoeuille (2020) demonstrate that the TWFE estimator is a weighted sum of the average treatment effects for each treated cell. For staggered designs in which treated units are not all exposed simultaneously, some of these weights can be negative. When treatment effects are not constant, negative weights can generate a TWFE estimate with a different sign than all of the constituent ATTs. Under the common trends assumption, the authors provide a method for recovering the weights placed on each ATT.

We run their diagnostic for the models in Table 2. We find that the sum and proportion of negative weights is -0.011 and 0.003 , respectively. This indicates that our TWFE estimate and the true ATT could only be opposite sign under substantial treatment effect heterogeneity. Specifically, $\beta_1 \approx 0.087$ and the standard deviation of weights of $\approx 6e^{-6}$ imply that the ATT can only be negative when the standard deviation of treatment effects across treated cells is greater than 10 thousand. We also find that these weights are not strongly correlated with cells’ population ($\rho = -0.01$) or luminosity ($\rho = -0.06$), two covariates that might generate treatment effect heterogeneity.

G.5.2 Goodman-Bacon (2021)

Goodman-Bacon (2021) shows that the TWFE estimator is a weighted average of all of the two-group (units with changing treatment status vs. all others), two-period (pre- and post-treatment) estimators in the data. They provide a method for decomposing the TWFE estimate for a particular sample, which allows us to discern which comparisons drive the overall result.

Table A.6 summarizes this decomposition for our sample.³³ Given the large number of untreated cells in our data, over 99 percent of the weight is placed on the comparison of treated vs. never treated cells. The averages of the treatment effect estimates are positive for all types of comparisons. This exercise alleviates concern that our results hinge on “forbidden comparisons” that use early-treated (or always-treated) cells as controls for later-treated cells. Such comparisons

33. We estimate Equation 1 with any ACLED battle as the outcome variable, an indicator for new pipeline construction (our treatment variable), and year fixed effects. This model generates results nearly identical to Table 2; the simplification permits us to run diagnostics which require considerable computational resources given the size of our data.

Table A.6: Goodman-Bacon (2021) TWFE Decomposition

Comparison	Total Weight	Average Estimate
Treated vs. Untreated	0.993	0.182
Later vs Always Treated	0.006	0.075
Later vs. Earlier Treated	0.001	0.084
Earlier vs. Later Treated	0.001	0.081

Table A.6 displays a decomposition based on Equation 1 of the implied weight assigned to two-by-two comparisons of treated units to untreated units, of those comparing later vs. always-treated units, of those comparing later vs. earlier-treated units, and those comparing units treated earlier vs. later. In addition, for each group, the average of the two-by-two estimates is presented. The regression predicts units with any ACLED battle as the outcome variable with an indicator for new pipeline construction (our treatment variable) and year fixed effects.

can be problematic if treatment effects change over time, as dynamic treatment effects imply a violation of the parallel trends assumption: counterfactually, cells switching their treatment status would not be expected to follow the same trend as already-treated cells. As the middle two rows of Table A.6 demonstrate, the TWFE estimator assigns little weight to these comparisons.

G.5.3 Callaway and Sant’Anna (2020)

Callaway and Sant’Anna (2020) provide a method for recovering disaggregated treatment effect estimates for each treated cell, which never use already-treated units as controls. These effects can then be aggregated in ways that avoid the use of negative weights or the down-weighting of early- or late-treated units — two issues that arise when using TWFE estimators to analyze staggered designs.

We use their method to generate two estimates of the overall ATT. First, we use weights proportional to the size of each treated cell: borrowing the authors’ notation, $\widehat{\theta}_W^O = 0.141 (0.034)$.³⁴ This “simple” aggregation overweights early-treated groups, which are observed over more post-treatment periods. Second, we average the effect across treated cells: $\widehat{\theta}_{sel}^O = 0.145 (0.049)$. Both estimates are quite similar to the TWFE estimate of $\widehat{\beta}_{fe} = 0.171$.

We next employ their method to generate an event-study plot, which shows the average treatment effect for units exposed to treatment for different lengths of time. Figure A.4 shows the dynamic effects for four years before and five years after the construction of a new oil or gas pipeline, with bootstrapped 90% confidence intervals adjusted for multiple testing. Parallel trends appear to hold in the pre-treatment period. The average effect does not differ dramatically by length of exposure.

34. As with Table A.6, we estimate Equation 1 with any ACLED battle as the outcome variable, an indicator for new pipeline construction (our treatment variable), and year fixed effects.

Figure A.4: Dynamic Effects of New Pipelines on the Probability of an ACLED Battle

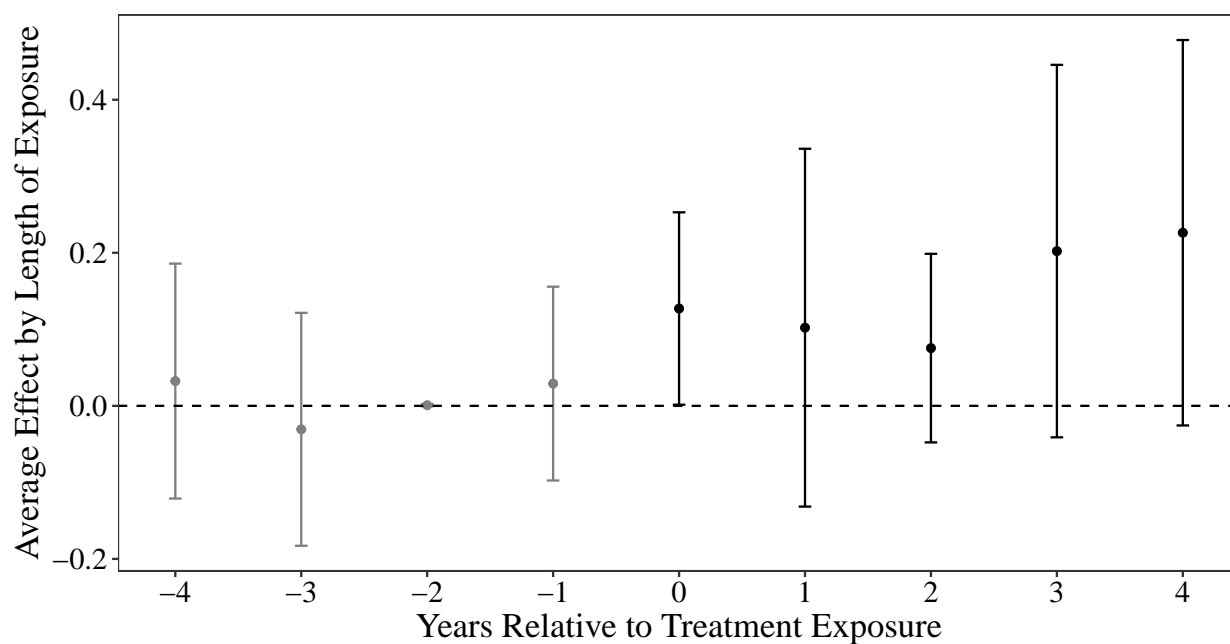


Figure A.4 displays a Callaway and Sant’Anna (2020) event-study plot, which shows the average treatment effect across different lengths of exposure to a new pipeline, with bootstrapped 90% confidence intervals adjusted for multiple testing.

H. Autoregressive Models of Conflict Near Pipelines

H.1 Alternative outcome data from EIAD

Table A.7: Predictive Power of Past EIAD Attacks (AR(2) Model)

	EIAD Attack	EIAD Attack on Oil	EIAD Attack on NG
t - 1	0.136 (0.061)	0.061 (0.049)	0.068 (0.120)
t - 2	-0.106 (0.051)	-0.101 (0.058)	-0.098 (0.033)
Sum of Coefficients	0.029 (0.075)	-0.041 (0.074)	-0.03 (0.087)
Cells	8,172	8,172	8,172
Country-Years	225	225	225
N	122,580	122,580	122,580

Table A.7: replicates the auto-regressive models in Table 8 using the Energy Infrastructure Attack Database (EIAD) to code whether an attack occurred in a given cell-year. Note that the EIAD ends in 2013, which reduces the sample size. Standard errors are clustered on cell.

Table A.8: Predictive Power of Past EIAD Attacks (AR(3) Model)

	EIAD Attack	EIAD Attack on Oil	EIAD Attack on NG
t - 1	0.148 (0.060)	0.073 (0.052)	0.056 (0.119)
t - 2	-0.121 (0.053)	-0.109 (0.056)	-0.098 (0.025)
t - 3	0.053 (0.072)	0.041 (0.069)	-0.075 (0.018)
Sum of Coefficients	0.08 (0.078)	0.005 (0.099)	-0.116 (0.113)
Cells	8,172	8,172	8,172
Country-Years	225	225	225
N	122,580	122,580	122,580

Table A.8: replicates the auto-regressive models in Table 9 using the Energy Infrastructure Attack Database (EIAD) to code whether an attack occurred in a given cell-year. Note that the EIAD ends in 2013, which reduces the sample size. Standard errors are clustered on cell.

I. Effect of Prices on Conflict Near Existing Infrastructure

I.1 Alternative clustering

Table A.9: Effect of Local and Global Fuel Prices on Armed Conflict around Existing Infrastructure with Alternative Clustered Standard Errors

	Battle	Rebel Battle	Rebel or Eth. Militia Battle
Log(Local Price) x Pipeline (γ_1)	0.065	0.110	0.106
S.E. clustered by ...			
5-km grid cells	(0.113)	(0.061)	(0.066)
10-km	(0.114)	(0.062)	(0.066)
20-km	(0.117)	(0.068)	(0.072)
Log(Global Price) x Pipeline (γ_2)	0.008	-0.117	-0.108
S.E. clustered by ...			
5-km grid cells	(0.083)	(0.057)	(0.060)
10-km	(0.082)	(0.057)	(0.059)
20-km	(0.088)	(0.066)	(0.067)
Equivalence Test ($H_0 : \gamma_1 = \gamma_2$) with S.E. clustered by ...			
5-km grid cells	p = 0.76	p = 0.05	p = 0.07
10-km	0.76	0.05	0.07
20-km	0.77	0.08	0.11
5-km Cells	1,464,041	1,464,041	1,464,041
10-km Cells	368,183	368,183	368,183
20-km Cells	92,731	92,731	92,731
Country-Years	536	536	536
N	17,216,229	17,216,229	17,216,229

Table A.9 presents a reanalysis of Table 4 using two alternative levels of clustering, 10x10-km clusters (containing four 5x5-km grid units of analysis), and 20x20-km grid clusters (containing 16 5x5-km grid units). Models estimated using OLS.

I.2 Alternative units of analysis

Table A.10: Effect of Local and Global Fuel Prices on Armed Conflict around Existing Infrastructure (10x10-km Grid Cells)

	Battle	Rebel Battle	Rebel or Eth. Militia Battle
Log(Local Price) x Pipeline	0.387 (0.308)	0.382** (0.168)	0.366* (0.203)
Log(Global Price) x Pipeline	-0.017 (0.223)	-0.291* (0.150)	-0.322** (0.163)
Equivalence Test ($H_0 : \gamma_1 = \gamma_2$)	0.41	0.03	0.04
Cells	366,444	366,444	366,444
Country-Years	536	536	536
N	4,309,190	4,309,190	4,309,190

Table A.10 presents a reanalysis of Table 4 with the units of analysis as 10x10-km grid cells rather than 5x5-km grid cells. Models estimated using OLS; standard errors clustered on 10x10-km grid cell. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

I.3 Alternative outcome data from EIAD

Table A.11: Effect of Fuel Prices on EIAD Attacks near Existing Infrastructure

	EIAD Attack	EIAD Attack on Oil
Log(Local Price) x Pipeline (γ_1)	0.143** (0.057)	0.142*** (0.050)
Log(Global Price) x Pipeline (γ_2)	-0.006 (0.024)	-0.009 (0.022)
Equivalence Test ($H_0 : \gamma_1 = \gamma_2$)	0.03	0.02
Cells	1,464,052	1,464,052
Country-Years	491	491
N	15,835,150	15,835,150

Table A.11 presents a reanalysis of Table 4 using the Energy Infrastructure Attack Database (EIAD) to code whether an attack occurred in a given cell-year. Note that the EIAD ends in 2013, which reduces the sample size. Models estimated using OLS with standard errors clustered at the grid cell level. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix References

- Barkat, Amiram. 2012. "Egypt rejects Bedouin pipeline demands; 'Globes' finds Sinai pipeline attacks are due to Bedouin tribes' demands for protection money from the Egyptian government." *Globes newspaper* (January).
- BBC. 2012. "Kurdish rebels blow up Iranian gas pipeline in Turkey." *BBC News* (October).
- Bozcali, Firat. 2011. "The Illegal Oil Trade Along Turkey's Borders." *Middle East Research and Information Project*.
- Callaway, Brantly, and Pedro HC Sant' Anna. 2020. "Difference-in-Differences with multiple time periods." *Journal of Econometrics*.
- Central Intelligence Agency. n.d. "Pipelines." CIA World Factbook.
- Comandancia general del Ejercito Popular Revolucionario. 1996. "White Water Manifesto." Press release archived by Centro de Documentación de Los Movimientos Armados.
- Comandancia military de zona del Ejercito Popular Revolucionario. 2007. "La Verdad Sobre Las Explosiones." Press release archived by Centro de Documentación de Los Movimientos Armados.
- Coskun, Orhan. 2015. "Attack halts flow in natural gas pipeline from Iran to Turkey." *Reuters* (July).
- Coskun, Orhan, and Humeyra Pamuk. 2015. "Turkey to boost security for energy infrastructure as PKK attacks rise." *Reuters* (August).
- Cuéllar, Alfonso. 2016. "Oil and peace in Colombia: Industry challenges in the power-war period." Wilson Center Latin America Program Report, January.
- El-Dalah, Moussa. 2010. "Letter from a Sinai Bedouin: We do not hate our homeland." *Egypt Independent* (July).
- De Chaisemartin, Clément, and Xavier d'Haultfoeuille. 2020. "Two-way fixed effects estimators with heterogeneous treatment effects." *American Economic Review* 110 (9): 2964–2996.
- Dube, Oeindrila, and Juan F. Vargas. 2013. "Commodity price shocks and civil conflict." *The Review of Economic Studies* 80 (4): 1384–1421.
- Dunning, Thad, and Leslie Wirpsa. 2004. "Oil and the political economy of conflict in Colombia and beyond: A linkages approach." *Geopolitics* 9 (1): 81–108.
- Goodman-Bacon, Andrew. 2021. "Difference-in-differences with variation in treatment timing." *Journal of Econometrics*.
- Hunn, David. 2017. "Mexican gasoline thieves steal \$1B from Pemex every year." *Houston Chronicle* (June).
- International Peace, Carnegie Endowment for. 2009. "The Kurdish Opening in Turkey: Origins and Future?" Brief note, December.
- Mahdavi, Paasha, Cesar B. Martinez-Alvarez, and Michael L. Ross. 2022. "Why Do Governments Tax or Subsidize Fossil Fuels?" *Journal of Politics* 84 (4): 2123–2139.
- McKinley, Jr., James C., and Antonio Betancourt. 2007. "With Bombings, Mexican Rebels Escalate Their Fight." *New York Times* (September).
- Pelham, Nicolas. 2012. "Sinai: The buffer erodes." Chatham House report, September.

- Peschar, Mariscal, Jacqueline, Maria Grisel Salazar Rebolledo, and Octavio Augusto Olea Gómez. 2021. “¿Qué sabemos del robo de combustible en México? Claroscuros de un delito que no cede.” *Revista mexicana de ciencias políticas y sociales* 66 (241): 245–280.
- Ross, Michael L., Chad Hazlett, and Paasha Mahdavi. 2017. “Global progress and backsliding on gasoline taxes and subsidies.” *Nature Energy* 2 (1): 1–6.
- Savran, Arin. 2020. “The Peace Process between Turkey and the Kurdistan Workers’ Party, 2009–2015.” *Journal of Balkan and Near Eastern Studies* 22 (6): 777–792.
- Staff. 2016. “Turkish police deal blow to PKK’s oil theft revenues.” *Daily Sabah* (January).
- Stocker, James. 2012. “No EEZ Solution: The Politics of Oil and Gas in the Eastern Mediterranean.” *Middle East Journal* 66 (4): 579–597.
- Sun, Liyang, and Sarah Abraham. 2021. “Estimating dynamic treatment effects in event studies with heterogeneous treatment effects.” *Journal of Econometrics* 225 (2): 175–199.
- Tobar, Hector. 2007. “A small guerrilla band is waging war in Mexico.” *Los Angeles Times* (September).
- Weiss, Andrew S., F. Stephen Larrabee, James T. Bartis, and Camille A. Sawak. 2012. *Promoting International Energy Security: Volume 2, Turkey and the Caspian*. Rand Corporation.